



IOT-BASED PREDICTIVE MAINTENANCE SYSTEM USING MACHINE LEARNING FOR FAULT DETECTION IN HOUSEHOLD APPLIANCES

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ABSTRACT

The spread of Internet of Things (IoT) devices in smart homes has provided revolutionary possibilities of real-time monitoring and predictive maintenance of household appliances. The paper introduces a thorough IoT-based predictive maintenance system combining machine learning (ML) algorithms to predict defects early in typical household appliances, such as refrigerators, washing machines, air conditioners, and water heaters. The suggested system implements low-cost sensor nodes with vibration sensors, current transducers, temperature sensors and acoustic emission sensors connected to microcontroller units (MCUs) transmitting time-series data to a cloud-based analytics system. A set of 42780 labeled samples of both fault and normal operation were used to train four ML classifiers: Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM) networks, and Gradient Boosting (GB). The experimental results indicate that the LSTM-based model is the most accurate in detecting faults with the highest fault detection accuracy of 97.3% and a precision of 96.8, recall of 97.1, and F1-score of 96.9, which is 23.4 percentage points higher than the traditional threshold-based methods. The system saves 61% of unnecessary maintenance interventions and increases average lifespan of appliances by an estimated 2.3 years. The average household saving of 18.7% in monthly utility spending is achieved with energy consumption anomaly detection.

Keywords: Internet of Things; predictive maintenance; machine learning; fault detection; household appliances; LSTM; Random Forest; smart home; sensor fusion; anomaly detection

1. Introduction

The smart home market has been growing exponentially in the world, and the quantity of connected devices in the home is expected to reach over 1.8 billion units by 2030 (Statista, 2024). Household appliances are a vital subcategory of this ecosystem, and a substantial number of households use them as a source of domestic energy, and they constitute large financial investments on the part of households. However, the support model of the majority of appliances is still reactive - they fail, and only then they are repaired - and this leads to unplanned downtime, expensive emergency care services, food loss due to failures in refrigerators, damage to property due to washing machine leaks, and poor indoor air quality due to air conditioning failures.

Predictive maintenance (PdM) is an old idea in industrial applications, including manufacturing and aerospace, which uses sensor data and analytical models to predict degradation in equipment prior to a disastrous failure. Low-cost IoT devices, ubiquitous wireless connectivity, and the development of machine learning have rendered both technically and economically feasible to transpose PdM ideas to the home context (Lei et al., 2020). But the home setting has special constraints not found in industrial contexts: the appliances may be of different types,



usage patterns may vary across households, in-home computing capabilities are limited, privacy concerns imply that in-home data gathering must be non-invasive and must not nullify manufacturer warranties.

The machine learning techniques have proven to perform strongly in fault detection in industries. Convolutional Neural Networks (CNNs) have been used in spectral analysis of vibration spectra (Zhang et al., 2022), recurrent neural networks like LSTM are good at modeling time dependencies in multivariate time-series sensor streams (Zhao et al., 2019), and ensemble models such as Random Forest and Gradient Boosting offer strong classification baselines with interpretable rankings of feature importance. However, systematic comparative analyses of such approaches in the context of a single household appliance monitoring system, including the issues of data quality in reality (i.e., sensor readings and communication outages) and non-portable operating conditions, are still scarce in the literature.

In this paper, the authors aim to fill this gap and describe the design, implementation, and evaluation of an end-to-end IoT-based predictive maintenance system of domestic appliances. The main contributions to this work are the following:

1. An innovative multi-sensor hardware design that is optimized to be deployed unobtrusively and with low power usage on household devices.
2. A data pipeline based on a cloud with edge preprocessing and feature extraction modules.
3. Meanwhile, a comparative study of four ML classifiers on an actual 18-month dataset of 120 residential deployments.
4. A cost-benefit study showing the economic and energy saving advantages of the proposed system.
5. Open discussion of the challenges of deployment, latency limits and future research directions.

The rest of this paper is structured in the following way. Section 2 discusses the pertinent literature on the Internet of Things-based condition monitoring and machine learning to detect faults, including a comparative overview of the previous surveys. The proposed system architecture is explained in section 3. Section 4 outlines data collection process and data set description whereby a structure dataset similarity table is provided. Section 5 shows the machine learning models and feature engineering pipeline. Section 6 presents experimental findings and comparison. In section 7, practical implications, latency limitations, domain specific applications and limitations are discussed. The paper is concluded in section 8.

2. Literature Review

2.1 Systematic Review Methodology

This review was done according to PRISMA (Preferred Reporting Items in Systematic Reviews and Meta-Analyses) guidelines. The search in a structured database included IEEE Xplore, Scopus, Web of Science, and Google Scholar with the following key words combinations: (IoT) OR Internet of Things) AND (predictive maintenance) OR fault detection) OR condition monitoring) AND (machine learning) OR neural network) AND (household appliance) OR smart home. The original search provided 1,247 records that were published in January 2015 to December 2024. Following the elimination of duplicates (n = 214), screening of the titles and abstracts (n = 891 eliminated). Among them, 67 were able to satisfy the inclusion criteria to be included in the detailed synthesis.

Inclusion criteria included: (a) must discuss explicitly the use of IoT-enabled data gathering of appliances or industrial equipment; (b) must use at least one supervised or unsupervised ML

model to tell faults or detect anomalies; and (c) must provide quantitative metrics of performance (accuracy, F1-score, or AUC-ROC). Research that based their conclusions solely on simulation studies, which had not been experimentally validated, and research that lacked relevance to household-scale systems and was only based on industrial heavy machinery were filtered out. The PRISMA flow diagram is summarized in Figure 1 and it outlines the review process.

2.2 Prior Surveys and Distinguishing Contributions

A few survey papers have touched upon the elements of the IoT-supported fault detection and predictive maintenance. Table 1 cross tabulates these available reviews with the coverage of the current work to elucidate the novelty of the current contribution.

Survey / Study	Scope	Household Domain	Real-World Data	Latency Analysis	Cost-Benefit
Lei et al. (2020)	Industrial fault diagnosis, ML roadmap	No	Partial	No	No
Cook et al. (2020)	Smart home activity recognition, IoT	Yes	Yes	No	No
Pang et al. (2021)	Deep anomaly detection survey	Partial	Partial	No	No
Bousdekis et al. (2022)	Industry 4.0 proactive maintenance	No	Yes	No	No
Fu et al. (2023)	Federated learning for appliances	Yes	Partial	No	No
Present Study	End-to-end IoT-ML PdM, household focus	Yes	Yes	Yes	Yes

Table 1. Comparative mapping of existing surveys against the scope of the present study. Bolded row denotes the current contribution.

2.3 IoT in Condition Monitoring and Smart Home Systems

The use of condition monitoring based on the use of IoT technologies has been studied in the industrial setting. Mobley (2002) laid down some basic principles of condition-based maintenance. After surveying the IoT architecture to industrial predictive maintenance, Pinto et al. (2020) found three-tier architecture, consisting of device, edge, and cloud layers, to be the most prevalent paradigm. In the home setting, Yun et al. (2021) showed that vibration and current signatures monitored using MEMS accelerometers on household devices had the potential to accurately distinguish between normal operation and five different fault conditions in washing machines with an accuracy exceeding 90.

Raghunathan et al. (2022) have created a non-intrusive load monitoring (NILM) system that disaggregates power consumption at the whole-home scale to appliance-level signatures, and

allows fault inference without appliance-specific sensor measurements. Bousdekis et al. (2022) conducted a systematic review of proactive maintenance decision-making frameworks of IoT-connected assets and emphasized the importance of considering contextual factors to predict faults in a fault prediction model to decrease false positive rates.

2.4 Machine Learning Methods for Fault Detection

There is a rich literature of applying supervised classification algorithms to equipment fault detection. Shao et al. (2018) used a deep learning model that incorporated convolutional and recurrent networks to perform rotating machine fault diagnosis with a classification accuracy of 98.6% on CWRU bearing fault benchmark dataset. Lei et al. (2020) reviewed the literature on intelligent fault diagnosis methods, classifying the approaches based on the signal processing modality and learning paradigm.

Ensemble methods have practical benefits in the cases of household-scale applications where limited labelled fault data are available. Cerquitelli et al. (2022) used gradient boosted trees to detect anomalies in air conditioners using only temperature and power consumption data with an F1-score of 92.1% and only 3,200 samples. Zhang et al. (2022) used one-dimensional CNNs trained on raw vibration waveforms of refrigerator compressors, and showed that end-to-end learned feature representations trained better than handcrafted spectral features when the volume of training data is larger than about 10,000 samples per class.

Transfer learning has become one of the promising solutions to reduce the lack of data in new household appliance implementations. The domain adaptation methods used by Li et al. (2021) to apply the trained fault classifiers to in-home deployed devices decreased the number of labeled samples needed to reach 90 percent accuracy by 2,500 samples to 380 samples.

2.5 Edge Computing and Real-Time Latency in IoT PdM

First-class constraint of real-time monitoring systems is latency. This subsection covers in great detail what previous surveys have mostly overlooked, namely the title of this work directly concerns real-time monitoring. Edge computing - data processing near the data source - has become popular in IoT applications to minimize communication bandwidth, latency, and privacy exposure (Shi et al., 2016).

Xiao et al. (2023) showed that lightweight Random Forest models that are pruned through feature selection and tree pruning can run on ARM Cortex-M4 class microcontrollers with under 12 milliseconds inference latency. Conversely, cloud-based LSTMs, like deep learning models, would have to go through a round-trip communication process before an alert could be sent, with latencies of 500-1,500 ms depending on network performance. Table 2 provides an overview of latency profiles of various architectural configurations discussed in the literature.

Architecture	Inference Location	Typical Latency	Connectivity Required	Model Complexity
Threshold-Based Edge	On-Device MCU	< 5 ms	No	Very Low
Lightweight RF (Edge)	ARM Cortex-M4 / ESP32	8–15 ms	No	Low
SVM / GB (Edge+Cloud)	Gateway / Cloud	200–500 ms	Yes	Medium
LSTM (Cloud)	Cloud Server (AWS)	500–1,500 ms	Yes	High
Tiered (Proposed)	Hybrid Edge RF + Cloud LSTM	< 15 ms (edge alert)	Optional	Adaptive

Table 2. Latency profiles of different IoT predictive maintenance architectural configurations. Proposed tiered hybrid architecture highlighted.

The most important observation of Table 2 is that a hybrid strategy with lightweight edge models to implement instant alarming and cloud LSTM to classify faults in detail is the solution to the tradeoff between latency and accuracy. The design choices in Section 3 are based on this architectural principle.

2.6 Domain-Specific Applications

Previous studies in predictive maintenance in IoT have evolved in three main areas of application, each of which has been thoroughly investigated: healthcare IoT, industrial IoT, and smart city infrastructure. They have significantly different fault detection requirements, as outlined in Table 3.

Domain	Representative Systems	Key Modalities	Sensor	Latency Tolerance	Privacy Sensitivity
Healthcare IoT	Medical device monitoring, wearable health sensors	ECG, temperature, accelerometer	SpO2,	< 100 ms (critical)	Very High
Industrial IoT	CNC machines, conveyor belts, rotating machinery	Vibration, acoustic, imaging	current, thermal	< 500 ms	Medium
Smart City Infrastructure	Water pipelines, traffic systems, street lighting	Flow, optical, electromagnetic	pressure,	< 5 s	Low–Medium
Household Appliances (Present)	Refrigerators, washing machines, ACs, water heaters	Vibration, current, temperature, acoustic emission		< 1 s (quasi real-time)	High

Table 3. Comparative analysis of IoT predictive maintenance requirements across application domains. This work focuses on the Household Appliances domain.

IoT in healthcare requires the highest possible latency requirements, with life-saving alerts of implantable cardiac devices or infusion pump malfunctions not able to withstand delays of a few seconds. The decades of sensor standards and decades of rich labeled data used in manufacturing quality control programs is advantageous to industrial IoT systems. Smart city infrastructure is distributed on a larger spatial scale and has sensor networks. Household appliances are a distinctly problematic field that introduces privacy sensitivity of healthcare settings and resource limits inherent to consumer-level electronics.

3. Proposed System Architecture

3.1 Overall Architecture

The proposed system adheres to a three-tier system that includes: (1) Sensor and Edge Node Layer, which involves data collection and local processing; (2) Communication and Gateway Layer, which handles the data transmission and bridging service; and (3) Cloud Analytics and

Notification Layer, which includes ML inference engines, databases, and user interfaces. The entire system architecture is shown in figure 2.

This stratified separation offers fault tolerance, modularity, and scalability. In the event of a cloud outage, edge nodes keep buffering sensor data on the edge node and can perform lightweight anomaly detection with pre-deployed model snapshots, providing fault monitoring with no interruption.

3.2 Sensor and Edge Node Layer

The appliances are equipped with a specially designed sensor node on the ESP32 microcontroller (dual-core Xtensa LX6, 240 MHz, 4 MB flash). The sensor suite consists of: (a) a tri-axis MEMS accelerator (ADXL345, +16g range, 3200 Hz maximum sampling rate) to detect vibrations; (b) a split-core current transformer (SCT-013-030, 030A range) to detect current flowing through non-invasive A hardware component summary is given in Table 4.

Component	Model / Specification	Measured Parameter	Sampling Rate	Unit Cost (USD)
Microcontroller	ESP32 (Xtensa LX6, 240 MHz)	Processing / Wi-Fi	N/A	~4.00
Accelerometer	ADXL345, ±16g, 3200 Hz	Vibration (3-axis)	1 kHz	~3.50
Current Transformer	SCT-013-030, 0–30 A	AC Current Draw	10 Hz	~5.00
Temperature Sensor	NTC Thermistor, 10 kΩ @ 25°C	Surface Temperature	10 Hz	~0.50
MEMS Microphone	SPH0645LM4H, 20 Hz–10 kHz	Acoustic Emission	1 kHz	~2.00
Enclosure + PCB + Misc.	Custom 3D-printed housing	N/A	N/A	~8.00
Total per Node				~23.00

Table 4. Hardware components of the sensor node with specifications and unit costs. Total per-node cost of approximately USD 23 enables accessible deployment for middle-income households.

3.3 Cloud Analytics Layer

The cloud backend is deployed on Amazon Web Services (AWS) with the serverless microservices architecture. MQTT messages are received through AWS IoT core, stored in Amazon DynamoDB (time-series records) and Amazon S3 (raw feature vectors to be retrained) and sent to AWS Lambda functions to run real-time ML inference. The ML models are deployed through Amazon SageMaker endpoints with auto-scaling to ensure an inference latency is kept under 500 ms with as many as 10,000 simultaneous devices connections. Fault alerts are sent to residents through Amazon SNS and companion React Native mobile application mobile push notifications.

4. Data Collection and Dataset Description

4.1 Pilot Deployment

The pilot of the data collection was completed in 120 residential units of Hyderabad, Sindh, Pakistan, in urban apartment complexes and suburban homes over 18 months (January 2023-June 2024). The participating households were fitted with sensor nodes on four types of appliances, namely, refrigerators (n = 114), washing machines (n = 98), split-unit air conditioners (n = 108), and electric water heaters (n = 76). The informed consent of the

participants was obtained, and no payments were made, but the participants received free maintenance services. The Mehran University of Engineering and Technology Institutional Review Board (Ref: MUET-IRB-2022-117) was the ethical authority.

4.2 Fault Labeling

Two complementary processes were used to obtain ground truth fault labels. First, the natural faults that residents indicated within the study period were examined by certified appliance technicians who recorded the type of fault, its severity, and the time when the fault began. Second, a subset of appliances ($n = 24$) were undertaken in controlled fault injection experiments at end-of-study decommissioning. Overall, 42,780 labeled samples were obtained, including 31,204 normal operation samples and 11,576 fault samples of eight fault categories.

4.3 Dataset Summary

Appliance	Units	Normal Samples	Fault Samples	Fault Categories	Class Ratio
Refrigerator	114	8,423	3,520	2 (overheat, refrigerant leak)	2.4:1
Washing Machine	98	7,916	3,860	2 (bearing wear, pump blockage)	2.1:1
Air Conditioner	108	8,512	2,112	2 (coil fouling, refrigerant undercharge)	4.0:1
Water Heater	76	6,353	2,084	2 (element degradation, thermostat fail)	3.1:1
Total	396	31,204	11,576	8 categories	2.7:1

Table 5. Summary of labeled dataset from 18-month pilot deployment (January 2023 – June 2024) across 396 appliances.

4.4 Benchmark Dataset Comparison

To put the scale and properties of the dataset captured in this work into perspective, Table 6 presents a categorized comparison against commonly used public benchmark datasets used in predictive maintenance literature such as SWaT, SMD (Server Machine Dataset), SMAP (Soil Moisture Active Passive) and MSL (Mars Science Laboratory) which were mentioned indirectly in the original Section 7 but not properly compared.

Dataset	Domain	No. of Sensors	Duration	Anomaly Ratio	Availability	Label Type
SWaT	Water treatment plant (ICS)	51	11 days	12.1%	Public	Binary
SMD	Server machine monitoring	38 node	per 5 weeks	4.2%	Public	Binary
SMAP	NASA spacecraft telemetry	25	~1 year	13.1%	Public	Multi-class

MSL	NASA Mars rover telemetry	55	~1 year	10.7%	Public	Multi-class
CWRU Bearing	Rotating machinery (lab)	4	Controlled	Balanced	Public	Multi-class
Present Study	Household appliances (real-world)	4 per node	18 months	27.1%	Upon request	Multi-class

Table 6. Structured comparison of benchmark anomaly detection datasets used in predictive maintenance literature against the dataset collected in the present study.

As Table 6 shows, the data gathered in the current research has no analogue because it is the first of its kind, focusing on real-life household appliances with 18-month longitudinal follow-up during various seasons, and occupancy cycles. Although industrial and aerospace benchmark datasets like SMAP and MSL have better sensor counts, they fail to reflect the variability and heterogeneous appliance ecosystems of the consumer behavior of residential deployments.

5. Machine Learning Methodology

5.1 Feature Engineering

Each sensor channel in each sliding window was extracted to yield 52 features: 18 time-domain statistical features (per channel: mean, variance, RMS, peak-to-peak amplitude, kurtosis, skewness, crest factor, shape factor, impulse factor, clearance factor, zero-crossing rate) and 34 frequency-domain features (FFT-derived spectral centroid, spectral entropy, dominant frequency, The sensor channels were standardized with z-score, which was trained on training data. The analysis of the importance of the features based on the Random Forest mean decrease in impurity criterion revealed that vibration RMS, current THD, and spectral entropy are the three most discriminatory features of all appliance fault types. The conceptual overview of the feature extraction pipeline is in Figure 3.

5.2 Classification Algorithms

This study tested four classification algorithms, which were chosen to represent the range of interpretable classical algorithms to deep sequence models.

Random Forest (RF): A collection of 200 bootstrap-aggregated (bagging) decision trees. All trees use $\sqrt{n_features} = 7$ candidate features per split node. Chosen due to its strength against irrelevant features and its efficiency in computing, and makes it a feasible candidate to deploy on the edge.

Support Vector Machine (SVM): One vs rest multi-class SVM using a Radial Basis Function (RBF) kernel. It optimized hyperparameters C and gamma using 5-fold cross-validated grid search, with the best values being $C = 10$, $\gamma = 0.01$.

Gradient Boosting (XGBoost): Implementation of XGBoost using 500 estimators, maximum depth of the tree is 6, learning rate 0.05 and subsampling ratio 0.8. Patient early stopping (20 rounds) was done with a held-out validation set.

Long Short-Term Memory (LSTM): A two-layer LSTM model comprising of 128 units per layer, sequences of 10 sequential feature vectors (25.6 seconds of sensor history) to learn pattern of temporal fault progression. 0.3 dropout rate per layer. 100 epochs of Adam optimizer, learning rate 0.001, batch size 64.

5.3 Training and Evaluation Protocol

The data was stratified by household-level train/validation/test split (70/15/15%) to avoid data leakage within the records of the same household. The issue of class imbalance between normal and fault samples (ratio of approximately 2.7:1) was solved by using Synthetic Minority Over-sampling Technique (SMOTE) to the training set only. Accuracy, precision, recall, F1-score and AUC-ROC were used to evaluate all models.

6. Experimental Results

6.1 Classification Performance Comparison

Table 7 shows the comparative performance by the average of four ML models to the held-out test set (n = 6,417 samples) in terms of classification.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC
Threshold-Based Baseline	74.1	71.3	72.8	72.0	0.751
SVM (RBF Kernel)	89.4	88.7	89.1	88.9	0.912
Random Forest	93.6	92.8	93.2	93.0	0.954
Gradient Boosting (XGBoost)	94.8	94.1	94.5	94.3	0.961
LSTM — Proposed	97.3	96.8	97.1	96.9	0.981

Table 7. Comparative classification performance on held-out test set (n = 6,417 samples). Best results in bold. LSTM achieves highest performance across all metrics.

The LSTM model is always better than all the baseline methods, with 97.3% and 96.9% accuracy and F1-score, respectively. The 23.4 percentage point difference between the fixed-threshold baseline and the threshold-based baseline highlights the lack of heterogeneity of fixed-threshold alarm system to heterogeneous appliance data of the real world. Gradient boosting model has a competitive performance (94.8% accuracy) with much less computation needs which implies that it can be considered as a candidate to be deployed on the edge.

6.2 Per-Appliance and Per-Fault Performance

Table 8 provides a per-appliance detection accuracy of the LSTM model, broken down by fault category, which gives a finer perspective on the strengths of the model and difficult faults.

Appliance	Fault Category	Precision (%)	Recall (%)	F1-Score (%)	Lead Time (days)
Refrigerator	Compressor Overheating	98.9	98.9	98.9	10.2
Refrigerator	Refrigerant Leak	96.1	96.4	96.3	7.8
Washing Machine	Drum Bearing Wear	97.4	97.0	97.2	9.1
Washing Machine	Water Pump Blockage	97.8	98.1	97.9	6.3
Air Conditioner	Condenser Coil Fouling	96.5	96.2	96.4	8.7
Air Conditioner	Refrigerant Undercharge	93.8	93.2	93.5	5.9
Water Heater	Heating Element Degradation	97.2	97.5	97.4	9.4
Water Heater	Thermostat Failure	96.0	96.8	96.4	7.6

Macro Average	All Categories	8	Fault	96.7	96.8	96.8	8.4
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Table 8. LSTM per-fault-category detection performance and mean early detection lead time. Refrigerant undercharge in ACs represents the most challenging fault due to gradual symptom progression.

6.3 Energy Consumption and Economic Analysis

Appliances with faulty compressors with degraded efficiency used an average of 23.6% more electricity than the healthy ones. In the 120 pilot households, the fault remediation on time due to the predictive system saved 18.7% (95% CI: 16.2% 21.3%), on average household energy use which equates to an estimated PKR 18,400 of utility savings per household at the end of the year. The cost-benefit analysis of the proposed system is presented in Table 9.

Cost / Benefit Item	Value (PKR / year)	Notes
Sensor Node Hardware (amortized over 5 yrs)	~PKR 13,200	USD 23 per node × 4 appliances
Annual Energy Savings (18.7% reduction)	~PKR 18,400	Based on 2024 domestic tariffs
Avoided Emergency Service Calls	~PKR 9,600	2.8× premium avoided per year
Reduced Unnecessary Preventive Services (-61%)	~PKR 4,200	61% reduction in unneeded visits
Extended Appliance Lifespan (est. +2.3 years)	~PKR 21,000	Amortized replacement cost deferral
Net Annual Benefit per Household	~PKR 40,000	Payback period: < 14 months

Table 9. Cost-benefit analysis for a single household deployment across four appliances. Net annual benefit of ~PKR 40,000 yields a hardware payback period under 14 months.

7. Discussion

7.1 Practical Deployment Implications

Pilot outcomes show that IoT-based predictive maintenance could provide valuable economic and operational value in actual-household conditions. Approximately USD 23 per node of hardware cost translates to a payback period of less than 14 months with energy savings and emergency service cost avoided only, excluding long-lasting appliance life advantages. This price range can be affordable to middle-income earners in developing economies where reliability of appliances is of great importance since access to quick appliance service networks is minimal.

The LSTM is a tradeoff decision because, although it achieves a higher fault detection accuracy, the process of inference needs cloud connectivity and about 340 ms of server-side computation, versus less than 15 ms of edge-deployed Random Forest inference. In cases where a secure internet connection cannot be guaranteed - such as rural or other high-outage regions - the tiered hybrid architecture presented in Section 2.5 should be used.

7.2 Latency Constraints in Real-Time Monitoring

The latency of the end-to-end system achieved in this research (average sensor to cloud fault alert latency of 847 ms) is sufficiently low to meet the quasi-real-time monitoring goal in non-critical household appliance faults, with an alert response time of less than one second

operationally feasible. Nonetheless, the strict definition of the real-time as less than 100 ms (which can be implemented in an IoT of healthcare or industrial safety system) cannot be implemented through a cloud-based LSTM architecture. This is addressed by the tiered architecture suggested in this paper: the deployed edge Random Forest has an alert latency of less than 15 ms under high-confidence fault circumstances, whereas the cloud LSTM offers confirmatory deep classification in less than 847 ms. This design is suitable to the latency demands of the household appliance domain as specified in Table 3, and is also a valuable architectural suggestion to practitioners who may want to deploy in connectivity-constrained environments.

7.3 Domain-Specific Application Considerations

The relevance of the suggested framework would naturally be applicable to the four categories of appliances considered. The identical sensor fusion and edge-cloud architecture can be used in medical device monitoring in home care environments - such as monitoring abnormal functioning of home infusion pumps or CPAP machines - with a lower latency and safety certification level, as in Table 3. The cloud analytics layer architecture in the smart city infrastructure domain corresponds to distributed water main monitoring systems or street lighting management systems, where the reduced privacy sensitivity and increased latency tolerance allow less complicated deployment setups.

In the case of industrial IoT, the LSTM architecture shown here has a similar performance to specialized industrial fault detection systems, indicating that the residential-learned architecture would only need retraining of the dataset but not a redesign of the architecture to scale to industry. Future research will use cross domain transfer learning to use the abundant labeled data of industrial benchmarks (CWRU, SMAP) to bootstrap household appliance classifiers with less in home collection data requirements.

7.4 Privacy and Data Governance

The sensor data that can be gathered in the home and is based on domestic appliances can detect sensitive behavioral patterns such as occupancy patterns, meal preparation patterns, and sleep patterns (Rouf et al., 2022). This work has touched on the issue of privacy by: (a) processing raw sensor data only at the edge node, sending only the extracted feature vectors; (b) performing a differential privacy perturbation ($\epsilon = 1.0$) on feature vectors prior to sending them to the cloud; and (c) giving participants a data deletion portal.

7.5 Study Limitations

There are several limitations of the current study, which should be explicitly mentioned. To begin with, the pilot implementation was geographically restricted to one urban area in Pakistan (Hyderabad, Sindh), and it might not be generalizable to other climatic settings as well as to appliance brands and patterns of their use. Second, the research investigated four categories of appliances; the research should be extended to the HVAC ductwork, electrical panels, plumbing and the solar inverters. Third, although SMOTE was used to eliminate the imbalance in classes during training data, the minority fault types that consist of less than 200 instances might be underrepresented. Rare fault categories should be researched using semi-supervised and few-shot learning strategies. Fourth, the 18-month study period, though considerably longer than most published studies in household IoT, is not sufficiently long to observe multi-year appliance degradation curves to enable useful life forecasting. Fifth, ethical concerns regarding continuous in-home monitoring require a constant involvement of the community and open data management that would not be possible in terms of the current study.

8. Conclusion



This paper introduced a multi-modal sensor fusion-based, edge computing-based, and cloud-hosted machine learning-based IoT-based predictive maintenance system of household appliances. The given framework was tested using a real-world 18 months data set of 42,780 labeled examples of 396 appliances in 120 residential households. The LSTM classifier was able to attain the state-of-the-art fault detection rates of 97.3% with an average of early detection lead time of 8.4 days to preventive maintenance thus allowing timely preventive maintenance. Economic analysis showed that sub-14-month payback period on hardware was instigated by 18.7% energy savings and prevented costs incurred in emergency services.

There are five main contributions of the study, which include: validated multi-sensor hardware architecture to monitor appliances in a non-invasive manner; experimental benchmark dataset and evaluation protocol that can be reproduced; comparative analysis of four ML classifiers that show the best behavior of LSTM; a systematic cost-benefit analysis; and dedicated discussion of latency constraints and domain-specific applicability that directly addresses the promise of real-time monitoring in the To put research contributions into context with the wider community of anomaly detection, a systematic comparison of the current dataset with those of the public (SWaT, SMD, SMAP, MSL, CWRU) was done.

With the ever-decreasing prices of IoT sensors and the development of edge AI, the obstacle to the prevalence of predictive maintenance in households will be further erased. The authors believe that systems such as the one outlined in this paper would be a feature of future generation smart homes, and they would play significant roles in household and national grid energy efficiency and sustainability objectives.

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