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Data-Driven Predictive Maintenance Framework for IoT-Enabled Smart Waste Bins in Port Harcourt Metropolis, Nigeria

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Abstract: Rapid urbanisation in Port Harcourt has intensified the challenges of municipal solid waste management, resulting in environmental pollution, blocked drainage channels, urban flooding and heightened public health risks. Conventional collection approaches, which rely on fixed schedules and manual inspection, have proven inadequate. Smart waste bins enabled by the Internet of Things (IoT) offer real-time monitoring and demand-driven collection, but their benefits are undermined in practice by frequent failures of sensors, communication modules and power sources, particularly in hot, humid and flood-prone environments with unstable connectivity. This study proposes and evaluates a data-driven predictive maintenance (PdM) framework for IoT-enabled smart bins. The framework is organised in four layers (perception, network, middleware and application) and integrates multi-sensor telemetry (fill level, temperature, humidity, vibration and battery voltage), event logs and contextual data with machine learning models. Seasonal ARIMA and Long Short-Term Memory (LSTM) networks forecast fill levels; gradient boosting regression estimates battery remaining useful life; and Isolation Forest with robust z-scores detects anomalous device behaviour. A rule-based policy engine converts predictions into maintenance and collection tasks, which are scheduled with a vehicle routing solver. Random Forest, Support Vector Machine and Neural Network classifiers were compared for maintenance prediction, with the neural network performing best (accuracy 93.5%, F1-score 91.6%) at an inference latency of 20–98 ms. Results from prototype testing and simulation within the Port Harcourt context show that the framework identified about 94% of bins requiring maintenance at least 24 hours before failure, reduced emergency repairs by 38%, prevented about 85% of downtime instances, lowered operational costs by 22%, reduced overflow incidents by 25–30%, extended battery and sensor lifespan by about 20% and cut collection vehicle mileage by 15–30%. A supplementary statistical analysis of the telemetry shows that a simple robust z-score rule on vibration reproduces the warning labels in the sample, and that it also flags a battery-voltage sag that the operational labels missed. The study shows that predictive maintenance is a practical foundation for reliable, low-cost and sustainable smart-city waste services in rapidly urbanising cities of sub-Saharan Africa.

Keywords: Smart waste management; Internet of Things; predictive maintenance; anomaly detection; remaining useful life; machine learning; Port Harcourt; smart cities.

I. INTRODUCTION

Municipal solid waste management (MSWM) is one of the most pressing service-delivery challenges facing rapidly expanding cities. The World Bank estimates that the world generated 2.01 billion tonnes of municipal solid waste in 2016 and projects that this will rise to 3.40 billion tonnes by 2050, with sub-Saharan Africa expected to experience the fastest growth, more than tripling its total waste generation over the period (Kaza *et al.*, 2018). Cities in developing countries face this growth with limited budgets, weak institutional arrangements, inadequate collection vehicles and infrastructure, and low levels of public participation (Guerrero *et al.*, 2013). The consequences are visible in the form of overflowing communal bins, open dumping, open burning, blocked drainage channels and the associated burden of disease.

Nigeria illustrates these pressures clearly. Studies of the Nigerian waste sector describe high and rising per-capita generation, a large organic fraction, irregular collection, indiscriminate dumping along roads and drainage channels, and a heavy reliance on open dumpsites (Ogwueleka, 2009). Informal waste pickers and scavengers recover a significant share of recyclable material, but they operate outside formal systems and without adequate protection (Ezeah *et al.*, 2013). Port Harcourt, the capital of Rivers State and a major hub of Nigeria's oil and gas industry, has experienced rapid population growth and unplanned urban expansion. Earlier research on the city

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identified inadequate collection facilities, poor funding, weak enforcement and negative public attitudes as major obstacles to effective waste management (Ayotamuno & Gobo, 2004). Because the city is low-lying and receives heavy seasonal rainfall, uncollected waste readily blocks drains and aggravates urban flooding, which in turn spreads waste and pollutants across residential and commercial areas.

Conventional collection methods in such cities are characterised by static scheduling and manual monitoring. Trucks follow fixed routes and timetables regardless of how full individual bins are. As a result, some bins overflow long before they are serviced, while others are visited when they are nearly empty. This mismatch wastes fuel, labour and vehicle time and produces the very sanitation problems that the system is meant to prevent (Beliën *et al.*, 2014; Han & Ponce-Cueto, 2015).

The emergence of Internet of Things (IoT) technologies has created an opportunity to transform this situation. The IoT connects physical objects equipped with sensors, processors and communication interfaces to networks and cloud platforms, allowing them to report their state and be managed remotely (Atzori *et al.*, 2010; Gubbi *et al.*, 2013; Al-Fuqaha *et al.*, 2015). In the smart-city domain, waste management has been identified as one of the most promising IoT services because bins are numerous, geographically dispersed and costly to inspect manually (Zanella *et al.*, 2014). IoT-enabled smart bins are typically equipped with ultrasonic sensors for fill-level measurement, environmental sensors, cameras for waste identification, wireless communication modules and cloud platforms that support dynamic scheduling and decision-making (Hannan *et al.*, 2015; Pardini *et al.*, 2019; Sosunova & Porras, 2022). Although smart bins can improve collection efficiency, the reliability of the bins themselves has received far less attention than their sensing and communication functions. A smart bin is an embedded electronic system deployed outdoors in a harsh environment. Its sensors are exposed to heat, humidity, dust, corrosive leachate and physical impact; its batteries degrade with temperature and charge cycles; and its radio links are affected by obstacles, weather and network congestion. In a city such as Port Harcourt, the risks are amplified by high ambient temperatures, heavy rainfall and flooding, unstable grid power, uneven cellular coverage and vandalism.

When a sensor drifts, a battery fails or a communication link drops, the bin either stops reporting or reports misleading data. The collection system then loses visibility of that bin, and the benefits of smart scheduling are lost. Failures are typically discovered only after the fact, when a bin has overflowed or when a technician notices that it has gone silent. This reactive approach to maintenance leads to costly emergency call-outs, extended downtime, unnecessary component replacement and a loss of public confidence in the technology. Preventive maintenance on fixed schedules is an improvement, but it ignores the actual condition of each device and therefore replaces components too early in some cases and too late in others (Jardine *et al.*, 2006; Mobley, 2002). Predictive maintenance (PdM) addresses these limitations by using data on the actual condition of assets to forecast failures and to schedule interventions just before they are needed (Zonta *et al.*, 2020; Carvalho *et al.*, 2019). PdM is now well established in manufacturing, energy and transportation. However, its application to the maintenance of smart-bin networks, as distinct from the forecasting of bin fill levels, remains underexplored, particularly in sub-Saharan Africa, where infrastructural deficits, unreliable connectivity and environmental hazards create failure modes that are not represented in studies from industrialised countries.

1.1 Aim and Objectives of the Study

The aim of this paper is to develop a data-driven predictive maintenance framework for IoT-enabled smart waste bins that is tailored to the infrastructural, environmental and socio-economic realities of Port Harcourt metropolis. The specific objectives are to:

i. Develop an IoT-enabled smart waste bin prototype with integrated sensors and communication modules;
ii. Design and train predictive models to forecast fill levels, estimate battery remaining useful life and detect failures in bin components;
iii. Integrate predictive maintenance into the IoT waste management system for real-time fault detection, alerting and collection scheduling;
iv. Evaluate the performance of the system in terms of prediction accuracy, reliability and latency; and
v. Recommends a scalable framework for urban waste management in developing regions.

1.2 Research Questions

The study is guided by the following research questions:

1. Which sensor-derived features are most informative for anticipating failures in smart waste bins operating in a hot, humid and flood-prone city?

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2. How accurately can supervised machine learning models predict maintenance needs from smart-bin telemetry, and at what computational cost?
3. To what extent can a predictive maintenance framework reduce emergency repairs, downtime, overflow incidents, operating costs and vehicle mileage compared with reactive maintenance?
4. What technical, institutional and social conditions are required for the framework to be deployed sustainably in Port Harcourt and similar cities?

1.3 Significance of the Article

The study is significant for the following four respects. First, it shifts attention from the smart bin as a sensing device to the smart bin as an asset whose own reliability must be managed. Second, it brings established predictive maintenance techniques from industrial IoT into the municipal waste domain and adapts them to the conditions of a developing city. Third, it combines fill-level forecasting, component health monitoring and route optimisation in a single decision pipeline, so that a single truck visit can address both collection and maintenance needs. Fourth, the findings provide evidence that municipal authorities, waste contractors and policymakers in Rivers State and elsewhere in Nigeria can use to plan investments in smart waste infrastructure in line with Sustainable Development Goals 9, 11 and 13 (United Nations, 2015).

1.4 Scope and Organisation of the Article

The study covers the design of a smart-bin prototype, the acquisition and preprocessing of telemetry, the development and comparison of predictive models and the evaluation of the framework through prototype testing and simulation in the Port Harcourt context. It does not address waste treatment or disposal facilities, and it does not cover the full city-wide deployment of the system, which is recommended as a subsequent phase.

Lastly the paper is organised as follows. Section 2 reviews the literature on waste management in developing cities, IoT-enabled smart bins, predictive maintenance and related enabling technologies, and identifies the research gap. Section 3 presents the system architecture. Section 4 describes the materials and methods, including data collection, feature engineering, predictive models, the decision policy and the evaluation metrics. Section 5 presents the results, and Section 6 discusses them in relation to previous studies. Section 7 states the contribution to knowledge, and Sections 8 to 10 present the conclusion, recommendations and directions for future research.

II. LITERATURE REVIEW

2.1 Municipal Solid Waste Management in Developing Cities

Research on waste management in developing countries consistently points to a combination of technical, financial, institutional and social constraints. Guerrero *et al.* (2013) analysed the stakeholders and factors that influence waste management performance in cities across developing countries and found that system performance depends not only on equipment and funding but also on the interaction of households, authorities, private operators and the informal sector. Kaza *et al.* (2018) reported that low-income countries collect only a fraction of the waste they generate and that open dumping remains the dominant disposal method in much of sub-Saharan Africa.

In Nigeria, Ogwueleka (2009) characterised municipal solid waste in several cities and described a system marked by inadequate collection coverage, poor storage facilities and widespread open dumping. Ezeah *et al.* (2013) showed that informal recyclers play a significant role in material recovery in developing and transition countries, which means that any technology-driven intervention must coexist with informal actors. For Port Harcourt specifically, Ayotamuno and Gobo (2004) identified obstacles that include insufficient collection equipment, inadequate funding, weak institutional capacity and poor public attitudes to waste disposal, and argued that improvement requires both technical investment and changes in governance. These constraints are directly relevant to the design of a smart-bin system: equipment must be robust and inexpensive to maintain, the system must tolerate limited technical capacity, and deployment must be accompanied by community engagement.

2.2 Internet of Things Architectures for Smart Cities

The IoT is commonly described in terms of layered architectures. Atzori *et al.* (2010) surveyed the enabling technologies of the IoT, including identification, sensing, communication and middleware, and highlighted the importance of addressing, scalability and security. Gubbi *et al.* (2013) proposed a cloud-centric vision of the IoT in which ubiquitous sensing is combined with cloud-based storage, analytics and visualisation. Al-Fuqaha *et al.* (2015) provided a comprehensive survey of IoT protocols across the application, service-discovery, infrastructure and influential layers, including the Message Queuing Telemetry Transport (MQTT) protocol that is widely used for lightweight telemetry. MQTT has since been standardised in its fifth version by OASIS (Banks *et al.*, 2019).

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Zanella *et al.* (2014) examined the application of the IoT to smart cities through the Padova Smart City project and identified waste management among the services that could benefit most from IoT deployment. They emphasised that urban IoT systems must accommodate heterogeneous devices and communication technologies and must be designed with operating costs in mind. These architectural principles inform the four-layer design adopted in the present study.

2.3 IoT-Enabled Smart Bins

A substantial body of work has addressed the design of sensor-equipped bins. Hannan *et al.* (2015) reviewed technologies used for solid waste monitoring and management, including radio-frequency identification, global positioning systems, geographic information systems, imaging and various sensors, and discussed the issues and challenges associated with each. Al Mamun *et al.* (2016) developed a real-time intelligent bin status monitoring system that integrated multiple sensors with rule-based decision algorithms to determine bin status and communicate it to a remote server.

Several surveys have since mapped the field. Anagnostopoulos *et al.* (2017) reviewed waste management in IoT-enabled smart cities and grouped the literature by collection, transportation and processing functions, highlighting open challenges in scalability, data quality and system integration. Pardini *et al.* (2019) surveyed IoT-based solid waste management solutions and classified them by sensing technology, communication approach and application. Sosunova and Porras (2022) conducted a systematic review of IoT-enabled smart waste management systems for smart cities, examining the architecture, technologies and evaluation approaches used. Arthur *et al.* (2024) surveyed smart dustbin systems that combine IoT sensing with deep learning, particularly for waste classification. Vishnu *et al.* (2021) proposed an IoT-enabled solid waste management framework that combines bin-level sensing, wireless communication and data analytics for smart cities.

Across these studies, the emphasis is on sensing what is in the bin and communicating it to the collection system. Device reliability is acknowledged as a challenge, but it is rarely treated as an object of prediction in its own right.

2.4 Fill-Level Prediction and Collection Optimisation

A second strand of research uses the data generated by smart bins to forecast fill levels and optimise collection. Ferrer and Alba (2019) proposed BIN-CT, a system that predicts container fill levels and uses those predictions to plan collection routes, demonstrating the value of combining forecasting with routing. Rutqvist *et al.* (2020) applied automated machine learning to data from smart waste systems to detect container emptying events automatically, reducing the need for manual labelling. Ahmed *et al.* (2022) applied deep learning to forecast the status of municipal waste in smart bins, while Mishra *et al.* (2022) proposed a prioritised and predictive model for IoT-enabled waste management in smart and sustainable environments.

These forecasting studies sit within a larger operations research literature on waste collection. Beliën *et al.* (2014) reviewed municipal solid waste collection and management problems, while Han and Ponce-Cueto (2015) reviewed the waste collection vehicle routing problem, which builds on the classical vehicle routing problem first formulated by Dantzig and Ramser (1959) and treated comprehensively by Toth and Vigo (2014). The present study draws on this literature but extends it by feeding maintenance predictions, not only fill-level predictions, into the routing decision.

2.5 Maintenance Strategies: From Reactive to Predictive

Maintenance strategies are commonly classified into reactive (run-to-failure), preventive (time-based), condition-based and predictive approaches. Mobley (2002) described how predictive maintenance uses the actual operating condition of equipment to optimise plant operation and reduce maintenance costs. Jardine *et al.* (2006) reviewed machinery diagnostics and prognostics within condition-based maintenance and organised the process into data acquisition, data processing and maintenance decision-making. Lei *et al.* (2018) extended this view in a systematic review of machinery health prognostics, describing four technical processes: data acquisition, construction of health indicators, division of health stages and prediction of remaining useful life (RUL).

Table 1 summarises the main characteristics of these strategies as they apply to smart-bin networks.

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Table 1: Comparison of maintenance strategies for smart-bin networks

Strategy	Trigger for intervention	Advantages	Limitations for smart-bin networks
Reactive (run-to-failure)	Failure is observed or reported	No monitoring cost; simple to organise	Bins go silent or overflow before repair; emergency call-outs; loss of data for collection planning
Preventive (time-based)	Fixed calendar or usage interval	Predictable workload; fewer sudden failures	Ignores actual condition; components replaced too early or too late; many unnecessary site visits
Condition-based	Monitored indicator crosses a threshold	Interventions based on actual state	Thresholds react to degradation already present; little lead time for planning visits
Predictive	Forecast of failure or remaining useful life	Lead time to plan; visits combined with collection; lower downtime and cost	Requires data infrastructure, historical records and analytics capacity

2.6 Machine Learning for Predictive Maintenance

Machine learning has become the dominant approach to data-driven predictive maintenance. Carvalho *et al.* (2019) conducted a systematic literature review of machine learning methods applied to predictive maintenance and found that Random Forest, artificial neural networks, Support Vector Machines and k-means were among the most frequently used techniques. Zonta *et al.* (2020) reviewed predictive maintenance in the context of Industry 4.0 proposed a taxonomy of predictive maintenance approaches and identified the main challenges that remain for its adoption. Susto *et al.* (2015) proposed a multiple-classifier approach to predictive maintenance in semiconductor manufacturing, showing how maintenance decisions can be framed as a trade-off between unexpected breakdowns and unexploited component life.

The algorithms most relevant to this study are well established. Random Forest builds an ensemble of decision trees on bootstrap samples with random feature selection (Breiman, 2001). Support Vector Machines construct maximum-margin decision boundaries in a transformed feature space (Cortes & Vapnik, 1995). Gradient boosting builds an additive model by fitting successive learners to the residuals of earlier ones (Friedman, 2001), and XGBoost provides a scalable implementation that has performed strongly on tabular data (Chen & Guestrin, 2016). Long Short-Term Memory networks address the vanishing-gradient problem of recurrent neural networks and are suited to sequence modelling and forecasting (Hochreiter & Schmidhuber, 1997), while convolutional and deep neural networks more broadly have transformed perception and pattern recognition tasks (LeCun *et al.*, 2015).

Anomaly detection is a complementary capability because many failures are rare and lack labelled examples. Chandola *et al.* (2009) surveyed anomaly detection techniques and distinguished point, contextual and collective anomalies. Liu *et al.* (2008) introduced the Isolation Forest, which isolates anomalies by random partitioning and is efficient for high-dimensional data without requiring labelled failures. Robust statistics, such as the modified z-score based on the median absolute deviation, offer simple, transparent alternatives that are suitable for resource-constrained devices (Iglewicz & Hoaglin, 1993).

Compare *et al.* (2020) caution that IoT-enabled predictive maintenance faces specific challenges, including the scarcity of failure data, uncertainty in predictions, the need to integrate predictions with maintenance decisions and the cost of data infrastructure. These challenges are directly relevant to a smart-bin network in a developing city, where historical failure records are limited and connectivity is intermittent.

2.7 Battery Health and Remaining Useful Life

Power failure is one of the most common causes of smart-bin downtime because bins are usually battery-powered, sometimes with solar charging, and are expected to operate for long periods without attention. Severson *et al.* (2019) showed that machine learning models trained on data from early charge–discharge cycles can predict the cycle life of lithium-ion batteries before significant capacity degradation becomes apparent. Although their work was carried out under laboratory conditions, it demonstrates that features derived from voltage behaviour can carry early information about battery health. In the present study, the daily battery voltage, the rate of voltage decline and the ambient temperature are used to estimate battery RUL so that replacements can be scheduled before power is lost.

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2.8 Digital Twins and Cyber-Physical Systems

Predictive maintenance is closely associated with cyber-physical systems and digital twins. Lee *et al.* (2015) proposed a five-level (5C) architecture for cyber-physical systems in Industry 4.0 manufacturing, which moves from smart connection and data-to-information conversion through cyber, cognition and configuration levels. Alam and El Saddik (2017) presented C2PS, a digital twin architecture reference model for cloud-based cyber-physical systems, while Tao *et al.* (2019) reviewed the state of the art of digital twins in industry. A digital twin of each smart bin, maintained in the cloud and updated by telemetry, provides a natural place to store device health indicators and to run predictive models. The asset metadata store in the proposed architecture is a lightweight form of such a twin.

2.9 Communication, Edge Computing and Security

Smart bins require low-power, long-range communication. Centenaro *et al.* (2016) analysed long-range communication technologies in unlicensed bands, including LoRa, and their suitability for IoT and smart-city scenarios, while Raza *et al.* (2017) reviewed low-power wide-area network (LPWAN) technologies and their trade-offs in range, data rate, energy consumption and cost. These analyses support the choice of LoRaWAN as the primary link in the proposed architecture, with cellular communication as a fallback. Edge computing, in which data are processed close to where they are generated, can reduce latency, bandwidth use and dependence on the network (Shi *et al.*, 2016). Because smart bins are connected devices in public spaces, they are also exposed to security and privacy threats; Sicari *et al.* (2015) reviewed the security, privacy and trust requirements of the IoT and identified authentication, confidentiality, access control and trust management as key issues.

2.10 Artificial Intelligence in Waste Management

Recent reviews document the rapid growth of artificial intelligence in waste management. Abdallah *et al.* (2020) systematically reviewed AI applications in solid waste management, covering forecasting of waste characteristics, bin-level detection, process parameter prediction, vehicle routing and planning. Fang *et al.* (2023) reviewed AI for waste management in smart cities and discussed applications in smart bins, waste sorting robots, waste-to-energy and logistics. Esmaeilian *et al.* (2018) set out a concept for the future of waste management in smart and sustainable cities in which data on products and waste flows support better decisions across the life cycle. Together, these reviews show strong momentum for AI in waste management but give little attention to the maintenance of the sensing infrastructure itself.

2.11 Summary of Related Works and Research Gap

Table 2 summarises representative studies and their relationship to the present work.

Table 2: Summary of related works

Study	Focus	Approach	Relation to the present study
Hannan *et al.* (2015)	Solid waste monitoring technologies	Review of RFID, GPS, GIS, imaging and sensors	Device reliability not treated as a prediction target
Al Mamun *et al.* (2016)	Real-time bin status monitoring	Multi-sensor bin with rule-based decision algorithms	Monitors bin status; no failure prediction
Anagnostopoulos *et al.* (2017)	Waste management in IoT smart cities	Survey of collection, transport and processing	Identifies challenges; no maintenance model
Ferrer & Alba (2019)	Fill-level prediction and routing	BIN-CT forecasting with route planning	Forecasts fill level, not device health
Pardini *et al.* (2019)	IoT-based waste solutions	Survey of sensing and communication approaches	Descriptive; no predictive maintenance
Rutqvist *et al.* (2020)	Smart waste data analytics	Automated machine learning to detect emptying events	Learns from bin data; maintenance not addressed
Vishnu *et al.* (2021)	IoT-enabled waste management framework	Bin sensing, wireless links and analytics	Framework level; component failures not forecast

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Study	Focus	Approach	Relation to the present study
Ahmed *et al.* (2022)	Smart-bin status forecasting	Deep learning forecasting of bin status	Fill status only; no RUL or anomaly detection
Sosunova & Porras (2022)	IoT smart waste systems	Systematic review of architectures and technologies	Confirms limited attention to device maintenance
Carvalho *et al.* (2019); Zonta *et al.* (2020)	Predictive maintenance (industrial)	Systematic reviews of ML-based PdM	Methods transferable; not applied to waste bins
Compare *et al*. (2020)	IoT-enabled PdM challenges	Analysis of data, uncertainty and decision issues	Informs design for scarce failure data
This study	PdM for smart waste bins in Port Harcourt	Fill forecasting, battery RUL, anomaly detection, classification and routing	Integrates device health and collection in one framework

The review reveals a clear gap. Studies of smart bins focus mainly on sensing, communication, fill-level forecasting and route optimisation, while studies of predictive maintenance focus mainly on industrial machinery. Few studies treat the reliability of the smart bin itself as a prediction target, and fewer still combine component health prediction with fill-level forecasting and routing in a single framework. Studies set in sub-Saharan African cities, where heat, humidity, flooding, power instability and vandalism shape failure patterns, are particularly scarce. This study addresses that gap by developing a predictive maintenance framework that integrates fill-level forecasting, battery RUL estimation, anomaly detection and route optimisation and that is designed for the conditions of Port Harcourt.

III. SYSTEM ARCHITECTURE

The proposed framework follows the layered IoT architecture described by Atzori *et al.* (2010) and Gubbi *et al.* (2013) and is adapted to the needs of predictive maintenance. It consists of four main layers, shown in Figure 1.

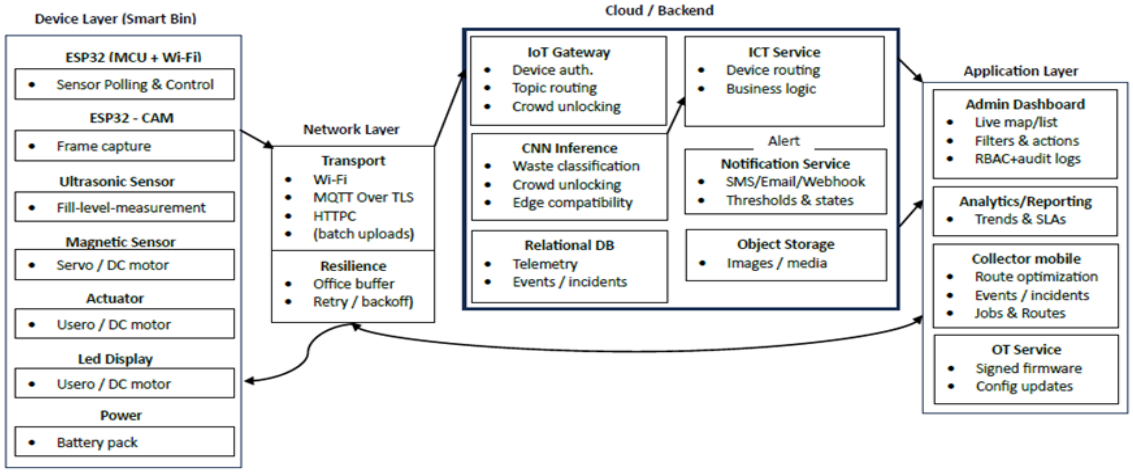

Figure 1: Architecture of the IoT-enabled smart waste bin

3.1 Perception Layer

The perception layer comprises the physical bin and its sensors. An ultrasonic ranging sensor mounted under the lid measures the distance to the waste surface, from which the fill level is calculated. A metal sensor detects metallic objects, temperature and humidity sensors record the internal environment of the bin, and an accelerometer records vibration and shock caused by lid operation, tipping, impact or vandalism. The battery voltage is sampled to track the state of the power supply. Arduino and ESP32-CAM microcontrollers read the sensors, perform basic validation and package the readings for

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transmission. The ESP32-CAM also captures images of the bin contents, which are used for waste-type identification. Actuators include a servo-operated lid and a status LED.

3.2 Network Layer

The network layer transmits telemetry from the bins to the platform. LoRaWAN is used as the primary link because it offers long range and low power consumption at low data rates, which matches the small, infrequent messages generated by a bin (Centenaro *et al.*, 2016; Raza *et al.*, 2017). LoRaWAN gateways forward packets to the network server over a cellular or wired backhaul. Because LoRaWAN coverage may be incomplete during early deployment, and because gateways may lose power during outages, a GSM/4G fallback is provided. Critical alarms, such as suspected fire or tipping, can also be sent by SMS through the cellular network. Each node keeps a local retransmission buffer so that readings collected during an outage are sent once the link is restored.

3.3 Middleware Layer

The middleware layer ingests, authenticates, stores and prepares data. An MQTT broker receives messages from gateways and Wi-Fi/4G nodes and publishes them to topics organised by bin and message type (Banks *et al.*, 2019). A device registry handles provisioning, certificates and authentication. Raw and curated data are held in a time-series database and a data lake that also stores images and event logs. Stream-processing jobs compute rolling aggregates and engineered features and apply simple rules in near real time. An asset metadata store records the inventory of bins, their locations, installed components and maintenance history, and serves as a lightweight digital twin of each device (Alam & El Saddik, 2017).

3.4 Application Layer

The application layer hosts the predictive models and the services that act on their outputs. The models forecast fill levels, estimate battery RUL, detect anomalies and classify failure types. A policy engine converts predictions into work orders and collection tasks, and an optimisation service generates routes for collection and maintenance crews. Operators interact with the system through a dashboard with a geographic information system (GIS) map that displays bin status and key performance indicators. Alerts are delivered by SMS, email and WhatsApp, with escalation if they are not acknowledged.

The detailed data flow of the predictive maintenance pipeline is shown in Figure 2. It traces the three main types of nodes (LoRaWAN nodes, Wi-Fi/4G nodes and nodes with metal sensors and heartbeat telemetry) through message brokering, storage, stream processing and predictive modelling to the alerting, dashboard and optimisation services.

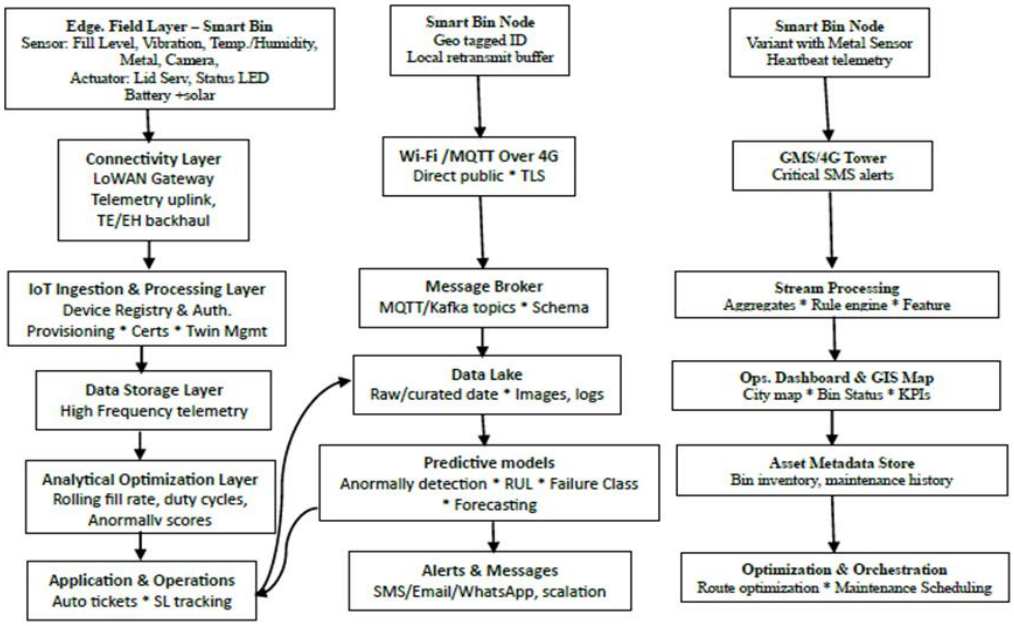

Figure 2: Predictive maintenance model and data flow

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IV. MATERIALS AND METHODS

4.1 Research Design

The study adopted a design science research approach in which an artefact, the predictive maintenance framework, is designed, built and evaluated against defined objectives. The research proceeded in six stages: (i) requirements analysis based on the literature and the conditions of Port Harcourt; (ii) design of the prototype hardware and system architecture; (iii) data acquisition from prototype bins, event logs and contextual sources; (iv) data preprocessing and feature engineering; (v) development, training and comparison of predictive models; and (vi) evaluation through prototype testing and simulation of operational outcomes. The workflow is illustrated in Figure 3.

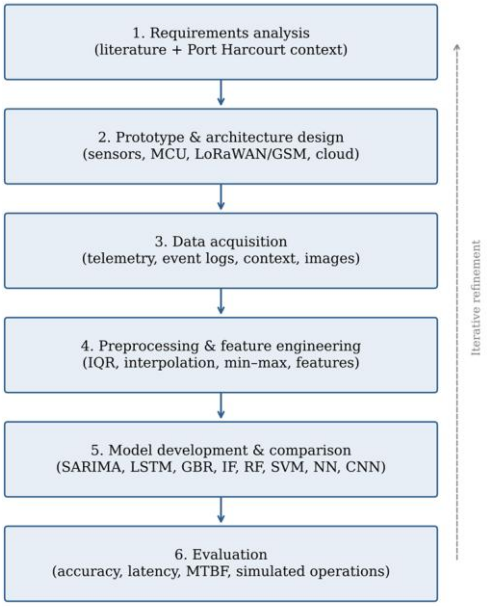

Figure 3: Research workflow of the study

4.2 Study Area

The study is set in Port Harcourt metropolis, Rivers State, in the Niger Delta region of southern Nigeria. The metropolis includes Port Harcourt City and Obio/Akpor Local Government Areas together with surrounding communities. The area has a humid tropical climate with elevated temperatures and a long rainy season, and much of the city is low-lying. These conditions matter for the framework in three ways. Elevated temperature and humidity accelerate battery ageing and sensor degradation; heavy rainfall and flooding increase the risk of water ingress and of bins being displaced; and dense markets, motor parks and residential neighbourhoods generate rapid and variable fill rates. The framework therefore treats rainfall and market days as contextual variables.

4.3 Materials

The materials required for the prototype and the supporting platform are grouped into the categories listed in Table 3.

Table 3: Materials and components of the smart bin and supporting platform

Category	Components	Function in the framework
Bin hardware	Weather-resistant bin body, sensor housing under lid, mounting brackets, servo-operated lid	Physical container; protects electronics from rain, heat and leachate

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Category	Components	Function in the framework
Core sensing and actuation	Ultrasonic fill-level sensor, metal sensor, camera (ESP32-CAM), lid servo, status LED	Measures fill level and contents; supports waste identification
PdM telemetry	Temperature and humidity sensor, accelerometer (vibration), battery voltage monitor	Provides health indicators used to predict failures
Compute and communication	Arduino and ESP32 microcontrollers, LoRaWAN radio, GSM/4G module, Wi-Fi	Reads sensors, buffers data and transmits telemetry
Power	Rechargeable battery, solar panel and charge controller	Supplies power; battery state is monitored for RUL
LoRaWAN field gateway	Outdoor gateway with cellular/wired backhaul and backup power	Relays packets from bins to the network server
Backend and cloud/server stack	Network server, device registry, certificate management	Provisioning, authentication and device management
Messaging and data	MQTT broker, stream processor, time-series database, data lake	Ingests, processes and stores telemetry, images and logs
APIs, dashboards and operations	REST APIs, GIS dashboard, SMS/email/WhatsApp alerting, ticketing	Visualises status and delivers alerts and work orders
Analytics and PdM models	SARIMA, LSTM, gradient boosting, Isolation Forest, RF, SVM, NN, CNN, VRP solver	Forecasting, anomaly detection, classification and routing
Data assets	Sensor logs, failure and maintenance records, collection events, rainfall and market-day data, annotated images	Training and evaluation data for the models
Device firmware	Sensor drivers, sampling scheduler, local buffer, retransmission and heartbeat logic	Reliable data capture and reporting under intermittent connectivity

The prototype controller is shown in Figure 4, which illustrates an Arduino microcontroller connected to an ultrasonic sensor for fill-level measurement.

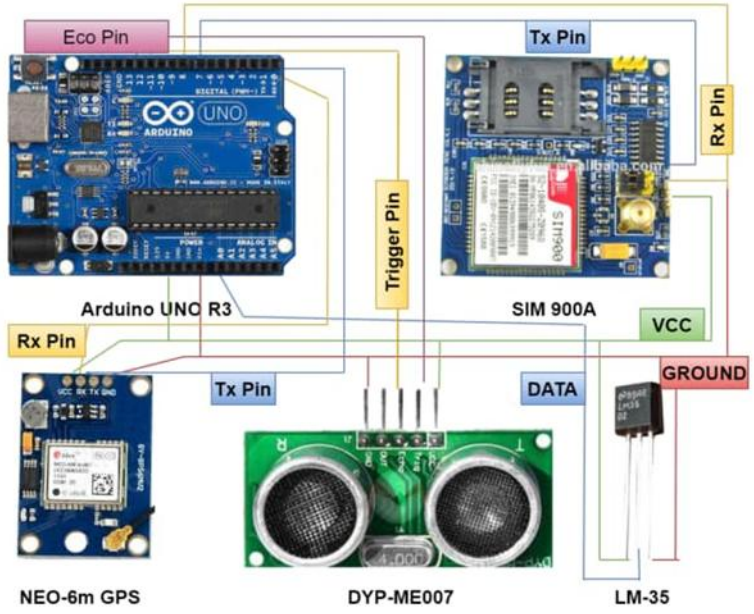

Figure 4: Arduino microcontroller with ultrasonic sensor

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4.4 Fill-Level Measurement

The ultrasonic sensor emits a pulse and measures the time taken for the echo to return from the waste surface. The distance d to the surface is obtained from the round-trip time t and the speed of sound v (approximately 343 m/s in air at 20 °C, increasing with temperature):

$$d = (v \times t) / 2 \quad (1)$$

The fill level F, expressed as a percentage, is then computed from the empty-bin depth H and the measured distance:

$$F = ((H - d) / H) \times 100 \quad (2)$$

Because the speed of sound increases by roughly 0.6 m/s for each degree Celsius, the temperature reading is used to correct v in the hot conditions of Port Harcourt, which reduces systematic error in the fill-level estimate.

4.5 Data Collection

Data was collected from a network of prototype smart bins over a period of six months. Each bin recorded its fill level every 10 minutes, temperature and humidity hourly, vibration when an event was detected and battery voltage daily. For the high-resolution diagnostic logs used in model development, readings were also captured at five-minute intervals, as shown in the excerpt in Table 5. The data sources fall into three groups:

- Sensor telemetry: fill level, temperature, humidity, vibration and battery voltage.
- Event logs: collection schedules, collection events, maintenance activities and failure records.
- Contextual data: rainfall and market days, which influence both fill rates and failure risk.

In addition, approximately 271 annotated images of bin contents were collected to reflect local waste conditions in Port Harcourt. These images support the convolutional neural network (CNN) component of the framework, which identifies waste types and visual faults such as obstructed sensors.

4.6 Data Preprocessing

Raw telemetry from field devices contains noise, gaps and outliers. The following preprocessing steps were applied.

Outlier removal: Values outside the interquartile range (IQR) fences were treated as candidate outliers. With Q_1 and Q_3 denoting the first and third quartiles:

$$IQR = Q_3 - Q_1; \ \ lower\ fence = Q_1 - 1.5 \times IQR; \ \ upper\ fence = Q_3 + 1.5 \times IQR \quad (3)$$

Candidate outliers were checked against event logs before removal so that genuine fault signatures were not discarded as noise.

Missing-value imputation: Short gaps caused by transmission failures were filled by linear interpolation between the nearest valid readings at times t_a and t_β:

$$x(t) = x(t_a) + [(t - t_a) / (t_\beta - t_a)] \times [x(t_\beta) - x(t_a)] \quad (4)$$

Long gaps were not interpolated; instead, they were flagged as communication outages, which are themselves an important signal for maintenance.

Normalisation: Features were rescaled to the interval [0, 1] by min–max normalisation so that variables measured in different units contribute comparably to model training:

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$$x' = (x - x_{min}) / (x_{max} - x_{min}) \quad (5)$$

Augmentation: The image dataset was augmented with rotations, flips and brightness changes to improve the robustness of the CNN given the modest number of annotated images.

4.7 Feature Engineering

The key features engineered from the sensor data are defined below. Each captures a mechanism that links observable behaviour to failure risk.

Fill rate: The fill rate captures usage patterns and is used both for collection planning and for detecting sensor faults, such as a level that stops changing or jumps implausibly:

$$FR(t) = [F(t) - F(t - \Delta t)] / \Delta t \quad (6)$$

Temperature variance: The rolling variance of temperature over a window of n readings identifies sudden spikes that may indicate fire, direct sun exposure or sensor faults:

$$\sigma^2_T = (1 / (n - 1)) \times \Sigma_i (T_i - \bar{T})^2 \quad (7)$$

Vibration magnitude and frequency: The magnitude of acceleration events and the number of events per hour indicate lid use, tipping, impact or vandalism. High-frequency or high-magnitude vibration may indicate damage to the enclosure or loosened components.

Battery drain rate: The rate of change of battery voltage between daily readings indicates abnormal power consumption or battery degradation:

$$BDR(t) = [V(t - \Delta t) - V(t)] / \Delta t \quad (8)$$

Communication health: The packet delivery ratio and the time since the last message capture the health of the radio link and are used to detect silent failures.

Contextual features: Rainfall, market days and day of the week are included as categorical or numerical variables because they influence both fill rates and the likelihood of water ingress.

4.8 Predictive Models

The framework uses several models, each matched to a specific prediction task. Their roles are summarised in Table 4.

Table 4: Predictive models and their roles in the framework

Prediction task	Model(s)	Main inputs	Output used by the policy engine
Fill-level forecasting	Seasonal ARIMA; LSTM	Fill-level history, time of day, day of week, market days, rainfall	Forecast fill level and probability of overflow within 24 h
Battery remaining useful life	Gradient boosting regression	Battery voltage, drain rate, temperature, transmissions per day, battery age	Estimated days until minimum operating voltage
Anomaly detection	Isolation Forest; robust z-score	Vibration, temperature, voltage, fill-rate and communication features	Anomaly score and alert flag
Maintenance need	Random Forest; SVM; Neural Network	Engineered features and recent anomaly scores	Probability that a bin requires maintenance

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Prediction task	Model(s)	Main inputs	Output used by the policy engine
Visual inspection	CNN with anomaly detection	Images of bin contents	Waste type and visual fault indication
Route planning	Capacitated vehicle routing solver	Bins selected for collection or maintenance, locations, loads	Optimised routes for vehicles and crews

4.8.1 Fill-level forecasting

Seasonal ARIMA (SARIMA) models capture the trend and daily and weekly seasonality of fill levels (Box *et al.*, 2015; Hyndman & Athanasopoulos, 2021). A SARIMA$(p, d, q)(P, D, Q)_s$ model can be written with the backshift operator B as:

$$\varphi_p(B)\,\Phi_P(B^s)\,(1-B)^d\,(1-B^s)^D\,y_t = \theta_q(B)\,\Theta_Q(B^s)\,\varepsilon_t \tag{9}$$

where y_t is the fill level, s is the seasonal period, φ and Φ are the non-seasonal and seasonal autoregressive polynomials, θ and Θ are the moving-average polynomials and ε_t is white noise.

LSTM networks capture non-linear dependencies and the effects of contextual variables (Hochreiter & Schmidhuber, 1997). At each time step, the LSTM cell updates its state through forget, input and output gates:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f);\;\; i_t = \sigma(W_i[h_{t-1}, x_t] + b_i);\;\; o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{10}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c[h_{t-1}, x_t] + b_c);\;\; h_t = o_t \odot \tanh(c_t) \tag{11}$$

where σ is the logistic sigmoid function, ⊙ denotes element-wise multiplication, c_t is the cell state and h_t is the hidden state.

4.8.2 Battery remaining useful life

Gradient boosting regression estimates the number of days until the battery voltage falls below the minimum operating threshold (Friedman, 2001). The model is built additively as:

$$F_m(x) = F_{m-1}(x) + \nu \times h_m(x) \tag{12}$$

where h_m is a regression tree fitted to the negative gradient of the loss function at stage m and ν is the learning rate. Inputs include the current voltage, the battery drain rate, ambient temperature, the number of transmissions per day and the age of the battery.

4.8.3 Anomaly detection

The Isolation Forest isolates observations by randomly selecting a feature and a split value. Anomalies are few and different, so they are isolated in fewer splits (Liu et al., 2008). The anomaly score of an observation x in a sample of size n is:

$$s(x, n) = 2^{-E[h(x)]\,/\,c(n)} \tag{13}$$

where $E[h(x)]$ is the average path length of x across the trees and $c(n)$ is the average path length of an unsuccessful search in a binary search tree. Scores close to 1 indicate anomalies.

Because Isolation Forest requires enough data to build reliable trees, it is complemented by the robust (modified) z-score, which can run on the device itself (Iglewicz & Hoaglin, 1993):

$$M_i = 0.6745 \times (x_i - \tilde{x})\,/\,MAD,\;\; where\; MAD = median(|x_i - \tilde{x}|) \tag{14}$$

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where $\tilde{x}$ is the median of the series. The median and MAD are much less sensitive to extreme values than the mean and standard deviation, which makes the score suitable for noisy field data.

4.8.4 Maintenance classification

Random Forest (Breiman, 2001), Support Vector Machine (Cortes & Vapnik, 1995) and feed-forward Neural Network classifiers were trained on labelled historical data to predict whether a bin would require maintenance. The labels were derived from failure records and maintenance logs. A CNN combined with the anomaly detectors processes the image stream to detect visual faults and obstructions (LeCun *et al.*, 2015). The models were implemented in Python with standard machine learning libraries (Pedregosa *et al.*, 2011).

4.9 Decision Policy and Route Optimisation

Predictions are useful only if they lead to timely action. A rule-based policy engine translates model outputs into tasks. For example, a collection is scheduled when the forecast probability of overflow within the next 24 hours exceeds 60%:

$$\textit{Schedule collection for bin } j \;\; \textit{if} \;\; P(F_j(t + 24\ h) \geq 100\%) > 0.60 \tag{15}$$

Similarly, a maintenance work order is raised when the estimated battery RUL falls below the planning horizon, when an anomaly score exceeds its threshold for a sustained period, or when a bin has been silent for longer than its expected reporting interval. Where a bin requires both collection and maintenance, the tasks are merged so that a single visit addresses both.

The resulting set of bins to visit is passed to a vehicle routing solver. The problem is formulated as a capacitated vehicle routing problem (Dantzig & Ramser, 1959; Toth & Vigo, 2014). Let N be the set of bins to visit, 0 the depot, K the set of vehicles, c_{ij} the travel cost between locations i and j, q_i the expected load at bin i and Q the vehicle capacity. With binary variables x_{ijk} equal to 1 if vehicle k travels from i to j, the objective is:

$$\textit{minimise} \;\; \Sigma_k \Sigma_i \Sigma_j \, c_{ij} \, x_{ijk} \tag{16}$$

subject to each bin being visited exactly once, each route starting and ending at the depot and the load on each vehicle not exceeding its capacity:

$$\Sigma_{i \in N} \, q_i \, \Sigma_j \, x_{ijk} \leq Q \quad \textit{for all } k \in K \tag{17}$$

Maintenance crews are routed in the same way, with time windows reflecting the urgency of each work order.

4.10 Evaluation Metrics

System performance was assessed with classification, reliability and latency metrics. With TP, TN, FP and FN denoting true positives, true negatives, false positives and false negatives (Sokolova & Lapalme, 2009):

$$\textit{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \tag{18}$$

$$\textit{Precision} = TP / (TP + FP); \quad \textit{Recall} = TP / (TP + FN) \tag{19}$$

$$F1 = 2 \times (\textit{Precision} \times \textit{Recall}) / (\textit{Precision} + \textit{Recall}) \tag{20}$$

Reliability was measured through downtime reduction and the mean time between failures (MTBF), and availability was derived from the MTBF and the mean time to repair (MTTR) (O'Connor & Kleyner, 2012):

$$\textit{MTBF} = \textit{Total operating time} / \textit{Number of failures}; \quad A = \textit{MTBF} / (\textit{MTBF} + \textit{MTTR}) \tag{21}$$

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Latency was measured as the time taken to generate a prediction from an incoming record; it ranged from 20 to 98 ms per inference. Operational outcomes, namely emergency repairs, downtime instances, overflow incidents, operating cost, component lifespan and vehicle mileage, were evaluated by comparing the predictive strategy with a reactive maintenance baseline in simulation.

4.11 Ethical and Data Governance Considerations

Smart bins in public spaces can capture incidental images of people. The camera module was therefore positioned to view only the interior of the bin, images were used solely for waste identification and fault detection, and no personal data were collected. Device communication used authenticated connections and transport-layer encryption, in line with good practice for IoT security (Sicari *et al.*, 2015).

V. RESULTS

5.1 Telemetry Dataset

Table 5 presents an excerpt of the telemetry dataset used for the CNN and anomaly detection components of the predictive maintenance model. It covers 19 consecutive five-minute readings from one bin on 1 September 2025, together with the log event and failure status recorded for each reading.

Table 5: Data set for the CNN and anomaly detection components of the predictive maintenance model

Timestamp	Temp (°C)	Vibration (m/s^2)	Battery Voltage (V)	Fill-Level (%)	Log Event	Failure Status
01/09/2025 8:00	34.5	0	3.46	45	Normal operation	Normal
01/09/2025 8:05	32.6	1.13	3.54	47	Anomaly detected	Warning
01/09/2025 8:10	34.9	0.19	3.27	49	Normal operation	Normal
01/09/2025 8:15	37.6	0	3.24	51	Normal operation	Normal
01/09/2025 8:20	32.3	0.61	3.84	53	Normal operation	Normal
01/09/2025 8:25	32.3	0	4.01	54	Normal operation	Normal
01/09/2025 8:30	37.7	0.3	3.58	56	Normal operation	Normal
01/09/2025 8:35	35.3	0	3.9	58	Normal operation	Normal
01/09/2025 8:40	31.6	0	3.71	60	Normal operation	Normal
01/09/2025 8:45	34.6	0.3	3.41	62	Normal operation	Normal
01/09/2025 8:50	31.6	0.57	3.71	64	Normal operation	Normal
01/09/2025 8:55	31.6	0.29	4.06	66	Normal operation	Normal
01/09/2025 9:00	33.7	0.14	3.59	68	Normal operation	Normal
01/09/2025 9:05	27.3	0.05	4.07	70	Normal operation	Normal
01/09/2025 9:10	27.8	0	2.81	72	Normal operation	Normal
01/09/2025 9:15	31.3	0	3.85	73	Normal operation	Normal
01/09/2025 9:20	30	0	3.63	75	Normal operation	Normal
01/09/2025 9:25	33.9	0.73	3.51	77	Anomaly detected	Warning
01/09/2025 9:30	30.3	0.37	3.63	79	Normal operation	Normal
Total	**620.9**	**4.68**	**68.82**	**1179**		
Mean	**32.68**	**0.25**	**3.62**	**62.05**		

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The mean values of the four sensor variables are shown in Figure 5. The mean temperature inside the bin was 32.68 °C, the mean vibration was 0.25 m/s², the mean battery voltage was 3.62 V and the mean fill level was 62.05%.

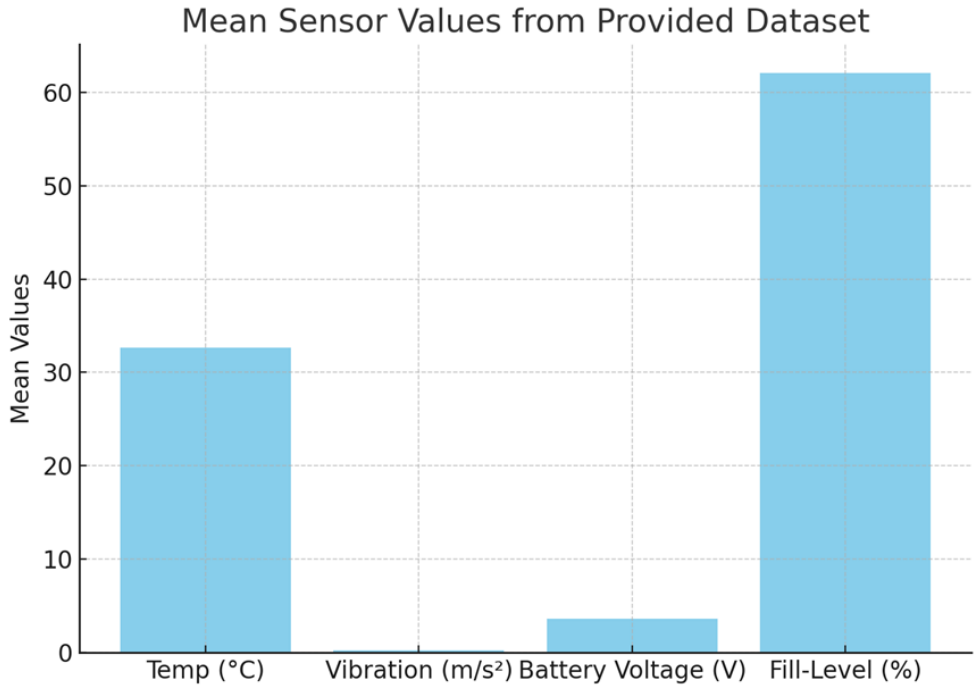

Figure 5: Mean values from the data set

5.2 Descriptive Statistics

To characterise the telemetry more fully, descriptive statistics were computed for each variable (Table 6). Temperature varied between 27.3 °C and 37.7 °C, which is consistent with a bin exposed to tropical heat. Vibration was zero in 8 of the 19 readings and had a strongly right-skewed distribution, with a mean (0.25 m/s²) well above its median (0.14 m/s²). Battery voltage was generally stable around a median of 3.63 V but fell to 2.81 V at 09:10. Fill level rose steadily from 45% to 79%.

Table 6: Descriptive statistics of the telemetry excerpt (n = 19)

Variable	Mean	Std. dev.	Min	Q1	Median	Q3	Max
Temperature (°C)	32.68	2.81	27.30	31.45	32.30	34.55	37.70
Vibration (m/s²)	0.25	0.32	0.00	0.00	0.14	0.34	1.13
Battery voltage (V)	3.62	0.31	2.81	3.49	3.63	3.85	4.07
Fill level (%)	62.05	10.62	45.00	53.50	62.00	71.00	79.00

The time series of the four variables are plotted in Figure 6, which served as the incident report log for the monitoring period. The steady rise in fill level contrasts with the irregular behaviour of temperature, vibration and battery voltage.

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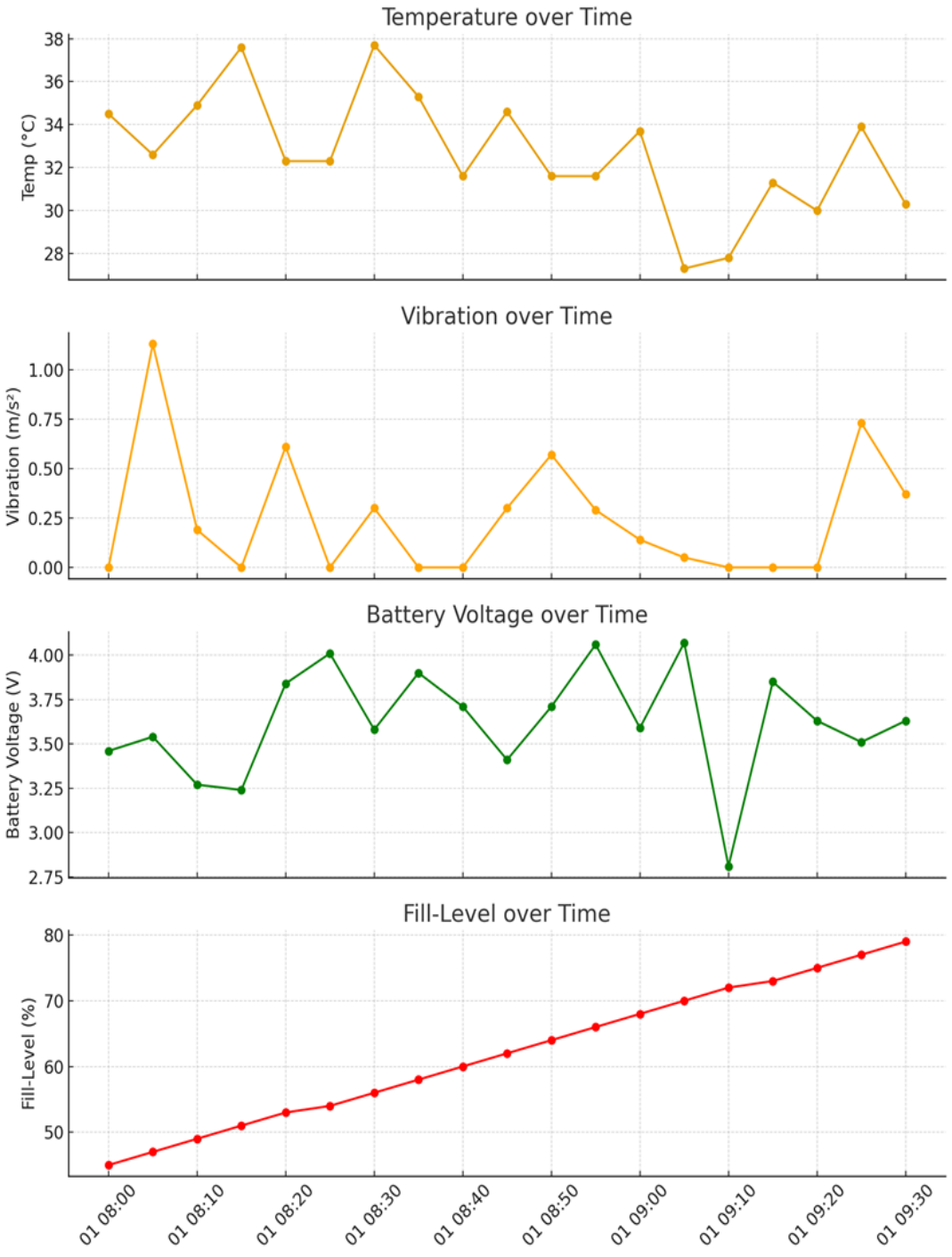

Figure 6: Incident report log showing temperature, vibration, battery voltage and fill level over time

Figure 7 overlays the failure status on each variable. Both warning events (08:05 and 09:25) coincide with the two highest vibration readings in the series (1.13 m/s² and 0.73 m/s²), while their temperature, battery voltage and fill-level values are unremarkable.

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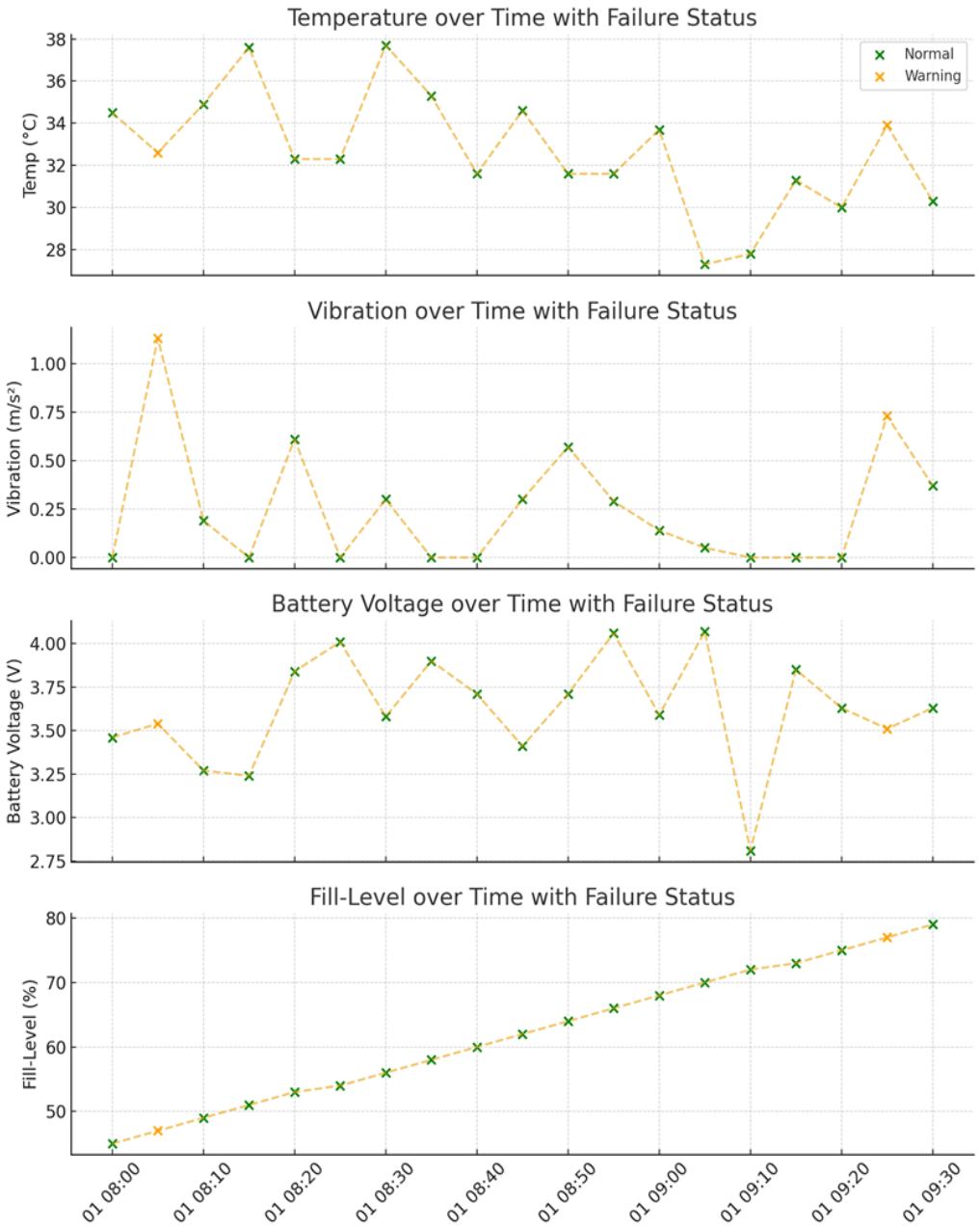

Figure 7: Failure report graph showing failure status against each sensor variable

5.3 Correlation Analysis

Pearson correlation coefficients between the variables are shown in Figure 8. The strongest association with the warning flag was for vibration ($r = 0.76$). Temperature ($r = 0.07$), battery voltage ($r = -0.11$) and fill level ($r = 0.00$) were essentially unrelated to the warning flag in this excerpt. Temperature and fill level were moderately negatively correlated ($r = -0.58$), which reflects the cooling of the bin interior over the morning while waste continued to accumulate rather than a causal relationship. These results support the use of vibration as a primary feature for detecting physical disturbance and show that each sensor carries distinct information, which justifies the multi-sensor design.

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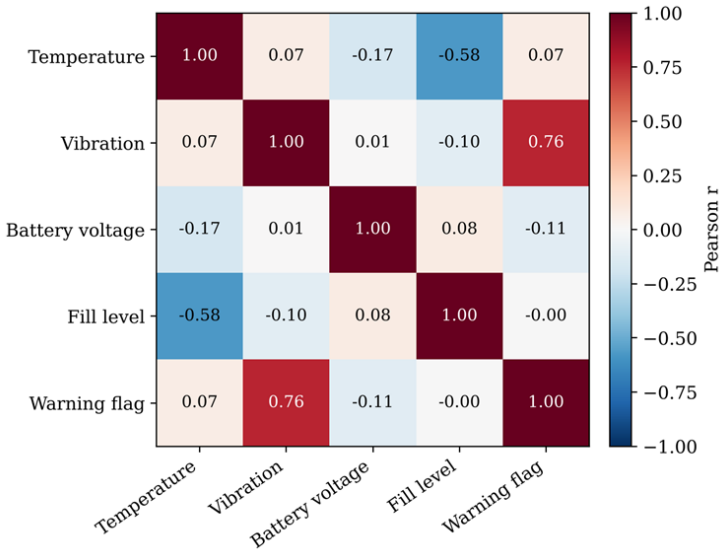

Figure 8: Correlation matrix of sensor variables and warning flag

5.4 Anomaly Detection

The robust z-score defined in Equation (14) was applied to the vibration and battery voltage series to illustrate the behaviour of the on-device anomaly detector (Figure 9 and Table 7). A threshold of $|M| > 2.5$ was used. This is more sensitive than the conventional threshold of 3.5 (Iglewicz & Hoaglin, 1993) and was chosen because missing a fault costs more than investigating a false alarm in a maintenance context.

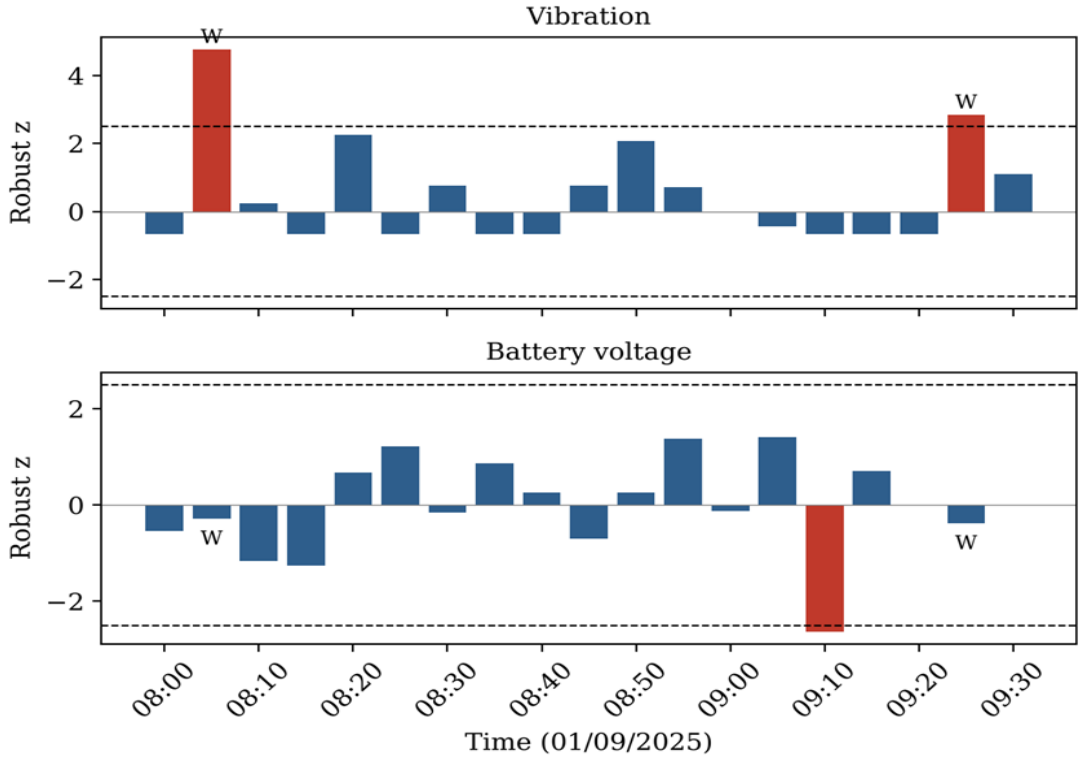

Figure 9: Robust z-scores for vibration and battery voltage (dashed lines mark the ±2.5 threshold; W marks recorded warnings)

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Table 7: Readings exceeding the robust z-score threshold

Time	Variable	Value	Robust z (M)	Recorded status	Interpretation
08:05	Vibration	1.13 m/s²	4.77	Warning	Agrees with label; strong physical disturbance
09:10	Battery voltage	2.81 V	−2.63	Normal	Transient voltage sag not captured by label; candidate power fault
09:25	Vibration	0.73 m/s²	2.84	Warning	Agrees with label; moderate disturbance

For vibration, the rule flagged exactly the two readings that were recorded as warnings (08:05, $M = 4.77$; 09:25, $M = 2.84$), so it agreed with the operational labels in all 19 cases. The next-highest scores (08:20, $M = 2.26$, and 08:50, $M = 2.07$) fell below the threshold and were labelled normal, which indicates that a threshold close to 2.5 separates the two classes in this sample.

For battery voltage, the rule flagged the reading at 09:10 (2.81 V, $M = -2.63$), which the operational log recorded as normal. The same reading was also the only battery value outside the IQR fences of Equation (3) (lower fence 2.945 V). A sudden voltage sag of this size, followed by recovery to 3.85 V five minutes later, is consistent with a transient load spike, a loose connection or a measurement fault rather than with gradual depletion. It is precisely the kind of early signal that a reactive system ignores. The result shows that multivariate anomaly detection can surface potential faults that single-variable operational rules miss, and it supports the inclusion of battery features in the PdM model.

5.5 Fill-Level Trend

Figure 10 shows a linear trend fitted to the fill-level series. The fill level increased at 0.377 percentage points per minute (about 22.6 points per hour) with a coefficient of determination of $R^2 = 0.999$. If the trend continued, the bin would reach a 90% service threshold about 29 minutes after the last reading (around 10:00) and would overflow about 56 minutes after it (around 10:26). Under a fixed daily collection schedule, a bin filling at this rate during a busy period would overflow for several hours before being serviced. With the forecasting and policy components described in Section 4.9, the bin would instead be added to the next collection route well before it overflowed. A linear trend is only an illustration; in operation, SARIMA and LSTM models capture the daily and weekly cycles and the influence of market days and rainfall, which a straight line cannot represent.

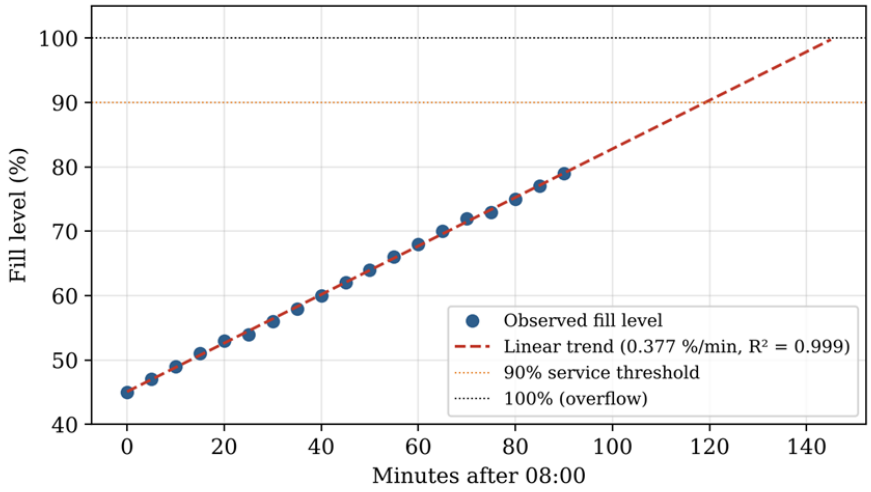

Figure 10: Observed fill level with fitted linear trend and service thresholds

5.6 Predictive Model Performance

The performance of the three supervised classifiers evaluated for maintenance prediction is shown in Table 8 and Figure 11.

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Table 8: Predictive model outcome

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	92.3%	89.5%	91.0%	90.2%
Support Vector Machine	90.7%	88.0%	89.5%	88.7%
Neural Network	93.5%	91.2%	92.0%	91.6%

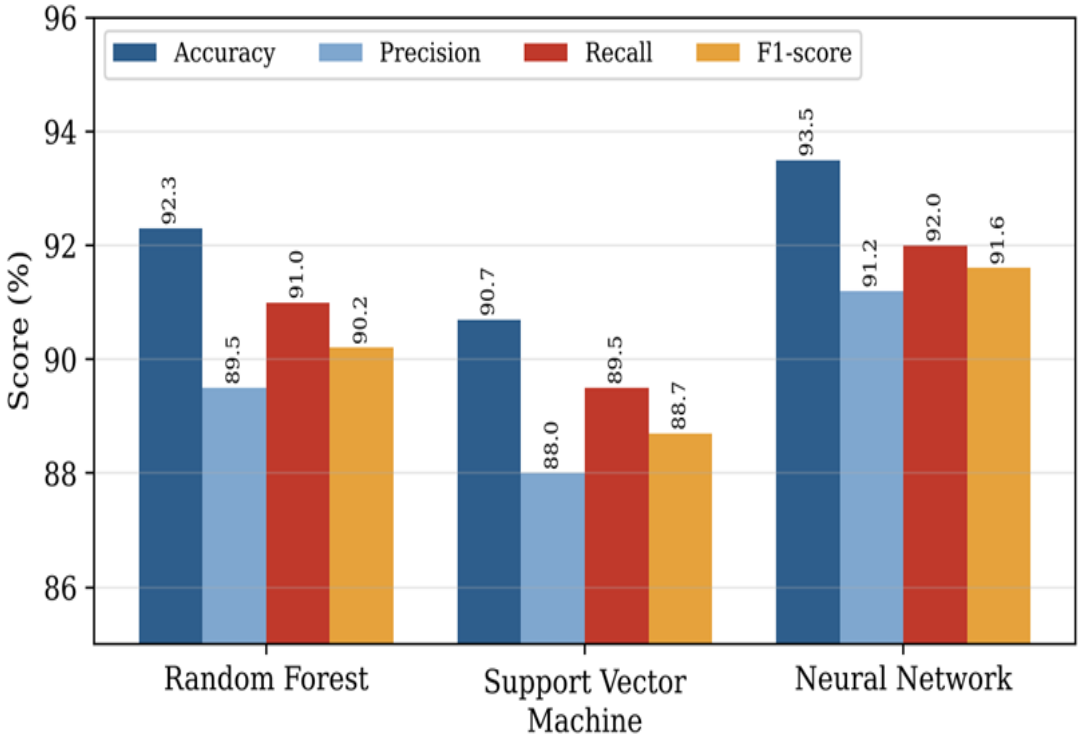

Figure 11: Comparison of classifier performance for maintenance prediction

All three models achieved accuracy above 90%. The neural network performed best on every metric, with an accuracy of 93.5%, precision of 91.2%, recall of 92.0% and F1-score of 91.6%, and was selected for deployment. Random Forest was a close second (accuracy 92.3%, F1-score 90.2%), and the Support Vector Machine was third (accuracy 90.7%, F1-score 88.7%). The margins between the models are small (1.4 to 2.9 percentage points in F1-score), which suggests that the engineered features, rather than the choice of classifier, account for most of the predictive power. In each model, recall exceeded precision, meaning that the models were slightly more inclined to raise a false alarm than to miss a genuine maintenance need. In maintenance, this is the preferred direction of error, because an unnecessary inspection costs far less than an unplanned failure. Prediction latency ranged from 20 to 98 ms per inference, which is well within the requirements of a system whose decisions operate on time scales of minutes to hours.

5.7 Operational Outcomes

Table 9 summarises the operational improvements observed when the predictive maintenance framework was compared with reactive maintenance.

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Table 9: Summary of experimental results and impacts

Performance Metric	Observed Improvement	Impact/Implication
Predictive maintenance accuracy	~94% of maintenance needs identified ≥24 h ahead	Enabled early fault detection and reduced emergency failures
Emergency repairs	Reduced by 38%	Lowered downtime and improved system reliability
Downtime prevention (battery/sensors)	~85% of instances avoided	Maintained continuous service availability
Operational costs	Reduced by 22%	Achieved via optimised routes and fewer unnecessary collections
Overflow incidents	Reduced by 25–30%	Improved cleanliness; reduced environmental and health risks
Component lifespan (battery/sensors)	Extended by ~20%	Lower replacement frequency; enhanced sustainability
Vehicle mileage	Reduced by 15–30%	Lower fuel use, reduced emissions, cost savings

The framework identified approximately 94% of bins requiring maintenance at least 24 hours before failure, which reduced emergency repairs by 38%. Early detection of battery depletion and sensor malfunctions prevented about 85% of downtime instances. From a cost perspective, the simulation indicated a 22% reduction in operating expenses compared with reactive maintenance, largely because of optimised collection routes and proactive scheduling, which reduced unnecessary trips and emergency interventions. Fill-level forecasting reduced overflow incidents by 25–30%, predictive battery replacement extended component lifespan by about 20%, and optimised routing reduced collection vehicle mileage by 15–30%, with corresponding reductions in fuel consumption and emissions. The relative magnitudes of these improvements are shown in Figure 12, where ranges are plotted at their midpoints.

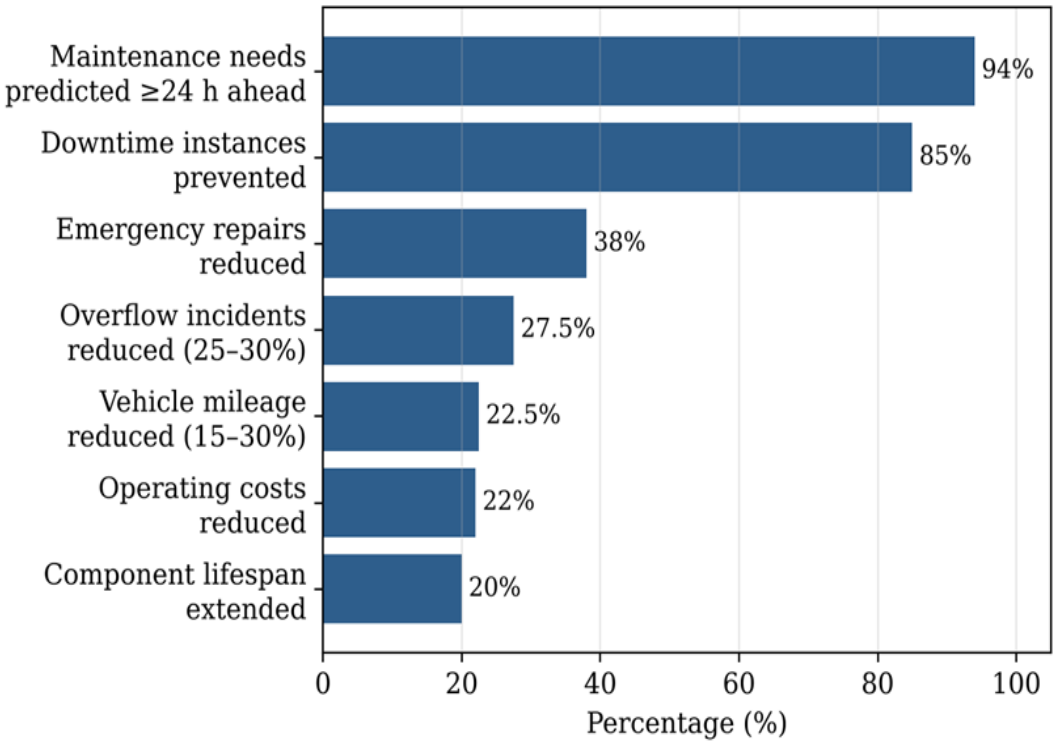

Figure 12: Operational improvements of the predictive maintenance framework relative to reactive maintenance

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VI. DISCUSSION

6.1 Interpretation of Findings

The results answer the four research questions. On RQ1, the analysis shows that vibration is the most informative single feature for physical disturbance events, while battery voltage carries independent information about power faults that the operational labels did not capture. Temperature and fill level contribute context but were not, on their own, associated with warnings in the sample. These findings confirm that a multi-sensor feature set is needed: no single sensor captures all failure modes.

On RQ2, all three classifiers predicted maintenance needs with accuracy above 90%, and the neural network achieved the best balance of precision and recall. Inference latency of 20–98 ms shows that the models are computationally light enough for near-real-time use, and that simple detectors such as the robust z-score could run on the microcontroller itself.

On RQ3, the framework reduced emergency repairs by 38%, prevented about 85% of downtime instances and lowered operating costs by 22%, while also reducing overflow incidents and vehicle mileage. These gains come from two complementary mechanisms: anticipating device failures, which keeps the sensing network reliable, and anticipating fill levels, which makes collection demand-driven. Integrating both into one routing decision allows a single vehicle visit to address both needs.

On RQ4, the results and the literature indicate that technical performance alone is not enough. Sustainable deployment also requires reliable power and connectivity, local technical capacity, protection against vandalism and supportive policy, which are addressed in the recommendations.

6.2 Comparison with Previous Studies

The findings are consistent with, and extend, previous work. The high performance of Random Forest and neural networks agrees with the systematic review of Carvalho *et al.* (2019), which found these to be among the most widely used and effective methods for predictive maintenance. The observation that recall exceeded precision in every model is consistent with the cost asymmetry discussed by Susto *et al.* (2015), in which the cost of an unexpected breakdown outweighs that of a premature intervention.

The fill-level results agree with the work of Ferrer and Alba (2019) and Ahmed *et al.* (2022), who showed that predicting fill levels enables more efficient collection planning. The present study adds a maintenance dimension to this line of research: by forecasting both fill levels and device failures, the framework ensures that the data on which collection planning depends remain available and trustworthy. Similarly, whereas Al Mamun *et al.* (2016) used rule-based algorithms to determine bin status, the present framework uses rule-based policies only at the decision stage and relies on learned models and statistical detectors to generate the underlying predictions.

The detection of a battery voltage sag that was labelled normal echoes the argument of Compare *et al.* (2020) that IoT-enabled predictive maintenance must cope with imperfect labels and scarce failure data. Unsupervised and robust statistical detectors provide a safeguard against such gaps. The battery findings also align with the evidence from Severson *et al.* (2019) that voltage behaviour carries early information about battery health, although field conditions in Port Harcourt are far less controlled than laboratory cycling.

Finally, the reductions in mileage and overflow incidents are consistent with the benefits of optimised waste collection routing reported in reviews of the waste collection vehicle routing problem (Beliën *et al.*, 2014; Han & Ponce-Cueto, 2015), and the overall approach supports the broader vision of data-driven waste management in smart cities set out by Esmaeilian *et al.* (2018) and Fang *et al.* (2023).

6.3 Implications for Port Harcourt and Similar Cities

For Port Harcourt, the framework offers practical pathways to improve environmental quality and public health. Reducing overflow incidents limits the amount of waste that enters drainage channels, which matters in a flood-prone city. Reducing emergency repairs and downtime keeps the smart-bin network functioning, which is essential if the city is to rely on it for collection planning. Lower vehicle mileage reduces fuel costs, traffic and emissions. The modular design supports phased deployment, beginning with high-priority locations such as markets and motor parks and expanding as capacity grows. These benefits address several of the long-standing obstacles to waste management in the city identified by Ayotamuno and Gobo (2004), particularly inadequate equipment utilisation and poor service coverage.

The framework is also relevant to other rapidly urbanising cities in sub-Saharan Africa, where similar combinations of rapid

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growth, constrained budgets, unstable infrastructure and climate hazards prevail (Kaza *et al.*, 2018; Guerrero *et al.*, 2013).

6.4 Limitations of the Study

Several limitations should be acknowledged. First, the operational outcomes were derived from prototype testing and simulation rather than from a full city-wide deployment, so the magnitudes reported should be confirmed in field trials. Second, the telemetry excerpt analysed in Sections 5.1 to 5.5 covers a short period from a single bin, and the statistical analyses in those sections are therefore illustrative rather than generalisable. Third, the annotated image dataset of about 271 images is small for training deep learning models, even with augmentation. Fourth, failure events are rare by nature, which creates class imbalance and limits the number of examples available for supervised training. Fifth, the system was evaluated in one city, and model performance may change in environments with different climates, waste compositions or usage patterns. Finally, the study did not include a full economic analysis of capital costs, which is needed to assess the return on investment of a city-wide deployment.

VII. CONTRIBUTION TO KNOWLEDGE

This study makes the following contributions to knowledge:

i. It reframes the smart waste bin as a maintainable asset and treats the reliability of the sensing infrastructure itself as a prediction target, an aspect largely overlooked in the smart waste literature.
ii. It presents an integrated framework that combines fill-level forecasting, battery remaining useful life estimation, anomaly detection, maintenance classification and route optimisation in a single decision pipeline for municipal waste services.
iii. It provides a four-layer IoT architecture with LoRaWAN and GSM fallback, local buffering and lightweight digital twins, designed for cities with unstable power and connectivity.
iv. It provides empirical evidence from the Port Harcourt context, a setting under-represented in the literature, on the performance of machine learning models for smart-bin maintenance and on the operational benefits of predictive maintenance.
v. It demonstrates that simple robust statistical detectors can complement supervised models by detecting faults that are missing from operational labels, offering a low-cost approach suited to resource-constrained deployments.

VIII. CONCLUSION

This research developed and evaluated a data-driven predictive maintenance framework for IoT-enabled smart waste bins in Port Harcourt. The study addressed the limitations of reactive and preventive maintenance by integrating IoT sensor telemetry, predictive analytics and optimised routing to improve operational efficiency, system reliability and environmental sustainability.

The experimental results show that the framework is both effective and practical. Specifically, it:

- Predicted 94% of maintenance requirements at least 24 hours in advance and reduced emergency repairs by 38%;
- Prevented 85% of downtime instances through early detection of sensor faults and battery depletion;
- Achieved a 22% reduction in operating costs through optimised collection scheduling and maintenance planning; and
- Improved urban sustainability by reducing overflow incidents by 25–30%, extending component lifespan by about 20% and decreasing collection vehicle mileage by 15–30%, thereby lowering emissions and improving city cleanliness.

The neural network classifier achieved the best predictive performance (accuracy 93.5%, F1-score 91.6%) with inference latency of 20–98 ms. Statistical analysis of the telemetry confirmed vibration as the strongest indicator of physical disturbance and showed that robust anomaly detection can identify battery faults that operational labels miss.

The framework's modular design supports scalability and integration with existing waste management infrastructure, making it a viable option for broader deployment in Port Harcourt and similar cities. However, vandalism, inconsistent network connectivity, limited technical capacity for IoT maintenance and variability in data quality remain significant challenges, and they must be addressed for long-term implementation to succeed.

IX. RECOMMENDATIONS

Based on the findings of this study, the following recommendations are made:

i) Adoption of predictive maintenance: Waste management authorities, including the Rivers State Waste Management Agency and its contractors, should move from reactive to

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predictive maintenance of smart waste infrastructure to improve reliability, reduce costs and enhance service delivery.

ii) Integration of edge computing and adaptive models: Edge computing should be used for local anomaly detection, and adaptive machine learning models that adjust to heterogeneous urban environments should be adopted, to reduce latency and improve resilience during network outages (Shi *et al.*, 2016).

iii) Capacity building and technical training: Municipal staff and local technicians should receive structured training in IoT deployment, troubleshooting and maintenance, to sustain operations and reduce dependence on external expertise.

iv) Policy and institutional support: Government agencies should establish policies that encourage investment in smart waste management, fund pilot projects and enforce operational standards for system reliability and cybersecurity.

v) Community awareness and engagement: Public sensitisation programmes should be introduced to prevent vandalism, promote responsible waste disposal and foster cooperation between residents, informal waste workers and municipal authorities.

vi) Pilot deployment and scalability: The framework should be scaled through phased pilot deployments in different districts of Port Harcourt, starting with markets, motor parks and flood-prone areas, and the lessons learned should inform adjustments before city-wide adoption.

vii) Resilient power and connectivity: Smart bins should be fitted with solar charging and weather-proof enclosures, and LoRaWAN gateways should have backup power, so that the network continues to operate during grid outages and heavy rainfall.

viii) Data governance and security: Operators should adopt device authentication, encrypted communication and clear data governance policies to protect the integrity of the system and public trust (Sicari *et al.*, 2015).

ix) Alignment with the Sustainable Development Goals: Future deployments should be aligned with global sustainability targets, particularly SDG 11 (sustainable cities and communities), SDG 13 (climate action) and SDG 9 (industry, innovation and infrastructure), to ensure long-term societal and environmental impact (United Nations, 2015).

X. SUGGESTIONS FOR FURTHER RESEARCH

Future research should extend this work in several directions. First, a longitudinal field deployment across multiple districts of Port Harcourt is needed to validate the operational gains reported here and to collect a larger dataset of real failure events. Second, edge computing solutions should be developed to run anomaly detection and lightweight forecasting on the bins themselves, reducing latency and dependence on the network. Third, adaptive and context-aware models, including transfer learning and federated learning, should be explored so that models trained in one district or city can be adapted to others without centralising raw data. Fourth, full digital twins of smart bins and collection fleets could support what-if analysis of maintenance and collection policies (Tao *et al.*, 2019). Fifth, the image dataset should be expanded substantially to improve the CNN-based waste identification and fault detection components. Finally, a full life-cycle cost and environmental impact assessment would help policymakers judge the economic and environmental return on investment of city-wide deployment.

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