

Predictive Maintenance for Critical Urban Infrastructure: A Multi-Stage Decision Framework Combining Temporal, Classification, and Anomaly-Based Analytics

Parveen Badoni

Department of Computer Science & Engineering, University Institute of Engineering,
Chandigarh University Mohali-140413, Punjab, India probhi.only@gmail.com

Komal

Department of Computer Science and Engineering, University Institute of Engineering,
Chandigarh University Mohali-140413, Punjab, India komalpotlia841@gmail.com

Sanjay Singla

Department of Computer Science & Engineering, University Institute of Engineering,
Chandigarh University, Gharuan, Punjab, India dr.ssinglacs@gmail.com

Priti Singla

Department of Computer Science & Engineering, University Institute of Engineering,
Chandigarh University, Gharuan, Punjab, India pritisingla04@gmail.com

Shilpa

Department of Computer Science, University school of computing, Rayat Bahra
University, Mohali, India Shilpam0525@gmail.com

Narinder Kumar

Department of Computer Science, University school of computing, Rayat Bahra
University, Mohali, India nk616319@gmail.com

Abstract— Earlier in many developing countries building roads, buildings and utility networks were the major problem but since from few decades maintaining them is more challenging. As cities grow rapidly the life span of the utilities is somehow shorter by ignoring the wear and tear warnings. Any such kind of oversight leads to disaster and costly repairs. In this paper the proposed a framework with the utilization of internet of things and artificial intelligence, which will predict whenever it demands any maintenance. For the monitoring and observation purpose this paper utilises three major components in the proposed framework LSTM, Random Forest Model, Anomaly detection. When it comes to decision making these three components prioritised the maintenance recommendation by looking at the likelihood and criticality of occurrence of each asset. For the testing part classification and forecasting metrices considered for the baselines models. The results mentioned in the paper highlights better accuracy and more comprehensive viewpoint using combined multiple approach analysis in comparison with a single model. The work in this paper paves way beyond the model architecture to the data driven management for further research in smart city infrastructural development. However as an outcome in future decision making will shift to more explainable data.

Keywords: *Anomaly Detection, Infrastructure Management, IoT, LSTM, Predictive Maintenance, Random Forest, Smart City*

1. INTRODUCTION

Rapid urbanisation puts roads, bridges, buildings, water systems and other critical infrastructure at ever growing risk [1-2]. Typical maintenance is reactive and leads to undesirable resource inefficiencies and unplanned failures. The Internet of Things (IoT) can sense, communicate and analyze data from physical assets continuously, making data-driven infrastructure management easier. Another area of well-studied topics is smart cities and cyber-physical systems, which can be used to tackle sustainable urban management by sensor technology, analytics and communication [3-5]. Predictive maintenance is a technique that relies on machine learning to identify trends that indicate degradation and to anticipate failures [6-8]. Though significant strides have been made in the field of predictive analytics, there are many systems that are currently being used that only serve a single service in the city or a single piece of equipment [9-10]. While the implementation of predictive maintenance systems in different urban infrastructures is still limited, the Indian research shows that the application of predictive maintenance systems based on IoT is possible in water management [11-12] and demand forecasting and in smart parking [13-15].

Other challenges to deployment at large scale are scalability, security, privacy and data management [16]. Most of the conventional methods are mainly temporal forecasting, anomaly detection & classification, independently. This limits their ability to leverage their ability to use multiple types of sensor data to make comprehensive maintenance decisions. While deep learning is a very useful way to enhance predictive capacity in time, it also can be more expensive and less interpretable. Thus, there is a need for infrastructure assessment, prediction of degradation and prioritization of infrastructure maintenance requirements using an integrated methodology to detect anomalies [17-20].

This paper focus on building an IoT based predictive infrastructure maintenance system, which combines the temporal prediction function of the LSTM network, the classification of the infrastructure condition using the Random Forest network and anomaly detection. The system can process various kinds of sensor data and provide suggestions for maintenance, ranked by priority. The scope is focused towards a data driven architecture that can be adapted to roads, bridges, public facilities and other smart city infrastructure for the future development of a robust and proactive urban maintenance system.

implementing IoT throughout a city is by no means easy, and this paper examines a number of the difficulties involved while suggesting methods to make predictive maintenance more reliable, efficient, and effective. Moreover, IoT provides an opportunity for residents to take part — for this reason our system features a citizen-reporting channel so that maintenance and problem-solving in the city become a joint endeavour rather than something carried out entirely behind the scenes.

Since cities are continuing to grow, the need to manage infrastructure properly, use resources in a sensible manner, and remain sustainable also increases as a result. Smart-city projects have provided new methods of dealing with this complexity, and the Internet of Things is at the heart of this trend comprising a network of devices that continuously monitor and interpret the conditions throughout the urban area. By making ordinary infrastructure smart, cities are able to respond to changing conditions as they occur rather than only after the fact.

Smart infrastructure monitoring system shown in figure 1 in which data being collected from roads, bridge, buildings and utility pipelines in cloud through edge gateways. Network of sensors are installed across various traffic signals, bridge structural vibration and stress, utilities, flow and pressure measures. All the real time or collected data filtered out at cloud platform for further analysis. Analysed data further be used in decision making whenever faults and abnormal operating conditions detected. To low down faults and failures, control centres helps to display the real time data through dashboards, this will help maintenance crew to repair the breakdown.

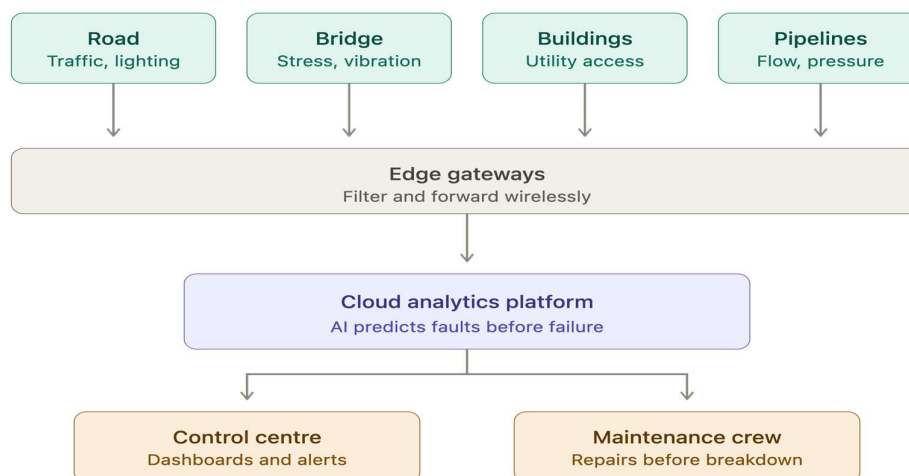


Fig. 1. Smart-city environment for IoT-enabled infrastructure monitoring

The paper contributes towards the IoT application on smart city under the urban development. For a smart city it is essential to connect all infrastructure and get the updates to the end user through mobiles. Once the operations is in the standard process then it is necessary to have a maintenance management.

2. LITERATURE REVIEW

As a result of the Internet of Things (IoT) research, ubiquitous sensing, connectivity and cloud-based analytics have been pointed out as some of the means to monitor the physical environment [21]. Based on this, architectures for heterogeneous sensing, networks and services in smart cities were developed using the Internet-of-Things (IoT) concept [22]. In addition to individual technological deployments, evaluations in the field of smart cities have pointed to a need for smart cities to be sustainable, which requires a mix of sensors, communication infrastructure, analytics and governance. Furthermore, there are other issues regarding interoperability, security, scalability and energy efficiency, but from cyber-physical system (CPS) viewpoints urban infrastructure is an interconnected system where sensing in real-time is at the heart of adaptive decision making [23].

Predictive maintenance (PdM) is preventive maintenance, but with the addition of pattern of degradation as derived from operational data. [24] presented Industry 4.0 PdM research covering techniques, standards and applications, whereas [25] systemically emphasized the importance of the machine learning (ML) techniques for failure prediction and highlighted that the operational context and the quality of the data has a significant influence on model selection. While useful, these studies include evidence that Random Forest, support vector machines, neural networks and ensemble methods can be useful, a lot of the results are applied to industrial machinery, rather than to a range of urban assets.

The recent studies around deep learning techniques using a multivariate time-series is becoming popular. [26] used the data set from NASA CMAPSS and their own data set for testing the method, which consisted of LSTM networks and dilated group convolution to characterize temporal and spatial associations in the IoT device data. The general trend of such models is to make the computation more complicated and less interpretable, but they may yield more accurate prediction results. Issues of privacy and generalizability also have been raised. [27] suggested an LSTM-Autoencoder for proactive maintenance for a heterogeneous smart-city infrastructure and encrypted model exchange using Federated learning. This approach addresses the issues with centralized data sharing, however, it is difficult to implement this approach in practice as it requires considerable coordination of computations and reliable distributed infrastructure.

In parallel, there are developments with digital twins that provide an added layer of decision support. In addition to the challenges of integration and standardisation, [28] also found that technologies such as IoT, AI and data analytics are enabling technologies. [29] argue that directly modelling industrial systems at city-scale is challenging as the city digital twin should be treated as a complex "system of systems. Despite the big opportunities offered by digital twins in simulation and predictive intervention, their ability to be synced with real assets is still challenging.

There is sufficient evidence of applications of Indian research. [30] have suggested to utilize IoT analytics for smart city projects in India with special emphasize on anomaly detection and monitoring of water. Vijai and Sivakumar experimented on the performance of ANN, DNN, ELM, LSSVM, Gaussian-process regression, Random Forest and regression models for water-demand forecasting, while [31] designed a smart-water system based on the Internet of Things (IoT). The studies presented here illustrate the usefulness of predictive analytics for Indian urban services but don't provide a single maintenance framework for a multitude of infrastructure classes; they are mostly domain-specific.

Anomaly detection in complex data streams, edge intelligence in latency-sensitive IoT applications, secure management of urban data, and deep learning-based prognostics for nonlinear degradation processes are among other recent works in the architecture domain of interest [32]. Many advances in sensing and prediction are illustrated in the literature, but there are some common challenges, including fragmented datasets, limited cross-domain validation, lack of understanding of a model, cost of computation, privacy issues, and a gap of connectivity between citizen observations and evidence generated by a sensor [33-34].

The main research gap lies in having a unified, scalable and understandable IoT-based framework that combines multiple types of urban sensor information with detection of anomalies, timeseries degradation prediction, infrastructure-condition classification, and citizen-observed information in a prioritized maintenance decision process. Research is typically limited to single prediction models, individual smart city services, or industrial assets. This is addressed through the proposed work which aims to develop an IoT sensing based resilient and proactive urban infrastructure management framework in which multi-source IoT sensing, state assessment using Random Forest, degradation prediction using LSTM, detection of anomalies, and prioritisation of maintenance are combined into a single framework.

3. METHODOLOGY

3.1. System Architecture

The layered IoT-based predictive maintenance pipeline the proposed framework follows is composed of sensing, communication, data processing, predictive analytics and decision support layers. Cities have heterogeneous sensors and visual data sources to track the urban assets such as highways, bridges and public infrastructure. The design is a blend of real-time monitoring and predictive control that is based on the smart-city IoT architectures. Predictive models generate maintenance recommendations when sensor measurements are submitted to a processing environment which is centrally located or cloud enabled by the use of suitable network infrastructure. This layered design is able to support interoperability, scalability and integration of diverse infrastructure data.

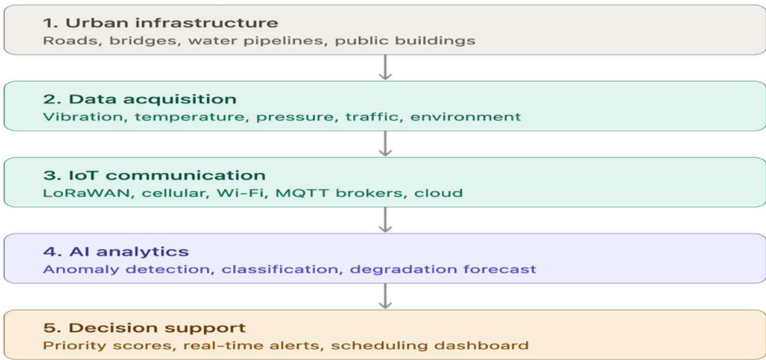


Fig. 2. Overall architecture of the proposed IoT-based predictive infrastructure maintenance framework

The figure 2 shows a step-by-step process for managing urban infrastructure. It starts with roads, bridges, water pipelines, and public buildings. Sensors collect information such as vibration, temperature, pressure, traffic, and environmental conditions. This information is transferred using technologies such as LoRaWAN, cellular networks, Wi-Fi, MQTT, and cloud systems. Finally, the results support maintenance decisions through priority levels, real-time alerts, and scheduling dashboards, helping authorities plan maintenance activities and respond to problems on time.

3.2. Data Collection and Preparation

The system uses multivariate time-series sensor data which can be in the form of traffic, environmental, structural and acoustic measurements. When available, infrastructure condition and maintenance records are added. Visual observations can also help to analyze the road-condition. Examples of data preprocessing include duplicate record elimination, missing data, time stamp synchronisation, noise reduction and normalisation of numerical attributes. According to the predictive-maintenance approach, time-series data are organized into successive windows in terms of time forecasting.

3.3. Model Selection and Feature Extraction

Statistical and time-based information is extracted using sensor streams (mean, variance, trend, rate of change and recent historical observations). Since the Random Forest can be applied to structured multivariate data, it is employed to categorise infrastructure-condition using random forest. The pattern of sequential sensor dependence and deterioration with time is modelled with LSTM networks. To find odd operational behaviour prior to failure escalation, anomaly detection is integrated. The diversity of urban infrastructure data is reflected in these complementary models.

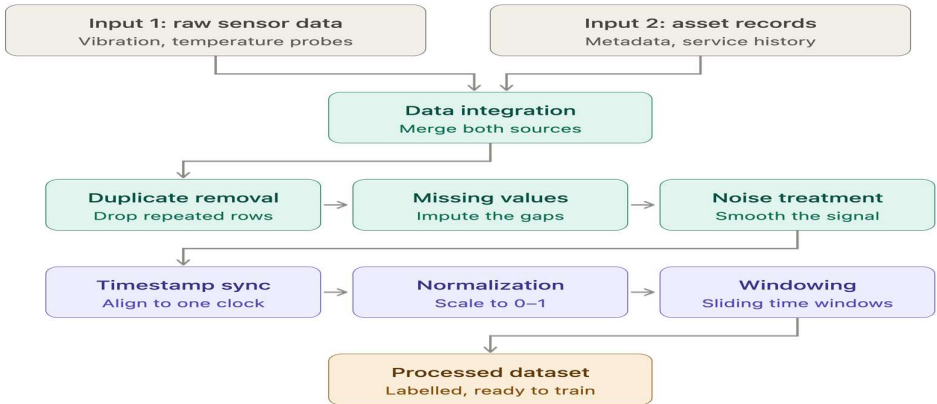


Fig. 3. Data collection and preprocessing pipeline for heterogeneous infrastructure data

Figure 3 above defines a data preprocessing pipeline for the predictive maintenance framework. Raw sensor data (vibration, temperature) and asset records (metadata, service history) are merged in the data integration stage. The combined dataset then passes through cleaning steps duplicate removal, missing-value imputation, and noise smoothing followed by preparation steps that align timestamps, normalize values to a 0-1 range, and segment the data into sliding time windows. The output is a labelled, processed dataset ready for model training.

3.4. Proposed Method / Core Module

The core module is integrated with degradation forecasting, anomaly detection, as well as condition classification. Preprocessing of incoming sensor data is done followed by its transformation to relevant features. Second, anomalous readings are found by an anomaly-detection stage. Third, the state of the infrastructure is categorised by Random Forest. The LSTM model forecasts the trend of future condition of assets considered to be potentially in bad conditions. The final outputs are combined with asset criticality with projected maintenance urgency to generate priority-based warnings. This combination method fills in the weaknesses of individual predictive models.

3.5. Implementation Details

It uses standard scientific and machine-learning libraries to preprocess, classify, deep learn and visualise the solution and Python to analyse the data and create the model. The end-to-end predictive-maintenance implementation structure of the experimental workflow includes data ingestion, model training, anomaly analysis, performance comparison and result visualisation. Streaming and cloud-based elements can be used to support real-time processing of scalable installations.

3.6. Evaluation Method

The suggested system will be evaluated with the help of train-validation-test partitions and comparative experiments with the baseline ML models. The performance in the classification will be determined by accuracy, precision, recall, F1-score, and ROC-AUC, and the performance in predicting will be determined by MAE, RMSE, and other measures of errors. There is also false-alert behaviour which we will investigate and computational efficiency. In order to determine the improvement of multi-stage analysis in terms of maintenance prioritisation and dependability, the integrated framework will be compared to single prediction models.

Figure 4 below shows six types of infrastructure feeding data into one central system. A bridge has strain and vibration sensors that track structural health, a road has traffic and environmental sensors that watch traffic flow, air quality, and noise, an underground pipeline has pressure and flow sensors that catch leaks, a public building has temperature and structural sensors for comfort and safety. A water treatment plant has pH and flow sensors for water quality. Every one of these sends its readings to a central IoT gateway. That gateway pulls the data together, converts it into a common protocol (MQTT, CoAP, or HTTP), and passes it on securely to a cloud platform, where it's stored and analyzed. From there, the results land on a control center dashboard that's where someone actually sees the live status, gets alerts, and makes decisions.

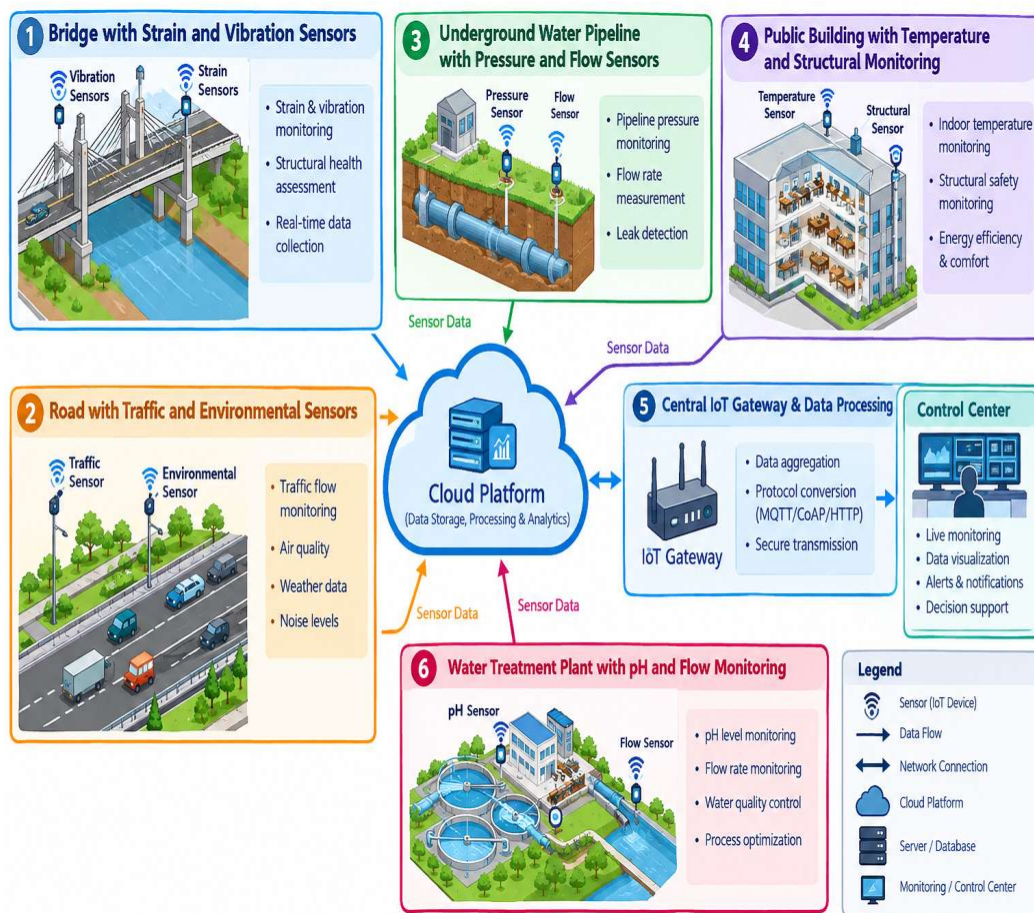


Fig. 4. IoT sensor deployment and heterogeneous data acquisition across urban infrastructure assets

4. EXPERIMENTAL CONFIGURATION

4.1. Dataset Overview

The experimental evaluation utilizes publicly available multivariate predictive-maintenance data, such as sensor observations of time series and equipment-condition data. Since they consist of sequential operational and sensor readings that are greatly utilized in predictive-maintenance studies, NASA CMAPSS-type degradation data are relevant to evaluate temporal prediction. Following smart-city IoT designs, the implementation also accommodates heterogeneous sensor streams, which characterize the environment, structure and operation of the city to enable the urban-infrastructure viewpoint. Rather than assuming this, the exact dataset subset, number of records and train test split should be provided directly out of the final implementation of the experiment.

4.2. Hardware and Software Setup

The Python implementation of the experiments is based on standard scientific computing and machine-learning packages to process data, construct models, and evaluate them. Although LSTM-based prediction uses a deep-learning architecture, the baseline models based on the use of random forests and similar models are built on a traditional ML architecture. The data manipulation and visualisation packages assist in data processing and analysis of results. The exact parameters (CPU, RAM, graphics card and operating system) of the machine it was run on during final execution should be documented since the experiments

are to be run on a standard computer system. This idea is similar to edge/cloud computing and scalable IoT analytics.

4.3. Baseline Models for Comparison

The proposed combined plan is compared to:

4.3.1. Random Forest, which is a strong ensemble-based classification

4.3.2. LSTM, which is deep temporal prediction

4.3.3. Standalone anomaly detection, which is anchored on accepted anomaly-analysis principles

4.3.4. Standalone predictive models without built-in prioritisation may be considered.

These baselines enable the comparison between the traditional machine learning, deep learning, and integrated predictive-maintenance techniques.

4.4. Evaluation Metrics

The classification performance is evaluated using accuracy, precision, recall, F1-score and ROC-AUC. Precision and recall are more important when there are unbalanced infrastructure failure classes. Time-series prediction and degradation forecasting are used when the MAE, MSE, RMSE and R2 are used when suitable. To evaluate the practical deployment viability, false-positive warnings and computing efficiency are also analysed.

4.5. Experimental Procedure

The first step is to create training, validation and testing partitions out of the cleaned and normalised raw sensor data. Second, in case of traditional ML and LSTM models, respectively, features and sequential windows are generated. Third, with proper conditions, the same data partitions are trained on baseline models. Fourth, the proposed framework incorporates autonomous processes of anomaly identification, condition classification and degradation forecasts. Finally, a comparison of the metrics used to evaluate each model is made, and the results are compared. Addressing the challenges of heterogeneous IoT data and city-scale implementation, this process is based on the established predictive-maintenance assessment processes.

5. FINDINGS AND DISCUSSION

The outcomes of the experiment show how well machine learning and deep learning techniques work for predictive maintenance with multivariate sensor data. The comparison between the Random Forest, LSTM and the anomaly-detection algorithms compares them using the categorisation and temporal prediction criteria proposed in the literature of predictive maintenance. Table 1 is the built-in system combines the steps of time and anomaly-analysis with the results of the Random Forest to categorise conditions. The Random Forest classifier achieved 100% accuracy, 99.68% precision, 99.89% recall, 99.78% F1-score and 100%.

TABLE I: COMPARISON OF PREDICTIVE MODELS' STATISTICAL PERFORMANCE

Model	Precision (%)	Accuracy (%)
LSTM	23.30	99.25
Random Forest	100.00	99.68
Proposed Integrated System	100.00	99.68

ROC-AUC in the implemented assessment. Figure 5 in comparison, the LSTM model showed excellent performance in temporal pattern recognition as it had 99.25% accuracy, 96.00% recall, and 98.52% ROC-AUC. Nevertheless, its claimed F1-score (43.71%) and precision (28.30) indicate how the imbalance of the classes affects it and how high the accuracy is not sufficient to measure predictive-maintenance reliability. The fact is in line with other studies that have seen the importance of precision, recall and F1-score in cases where failure events are relatively rare. Consequently, Random Forest provides a strong classification aspect, and LSTM can continue to help in the simulation of the progressive decline and life expectancy.

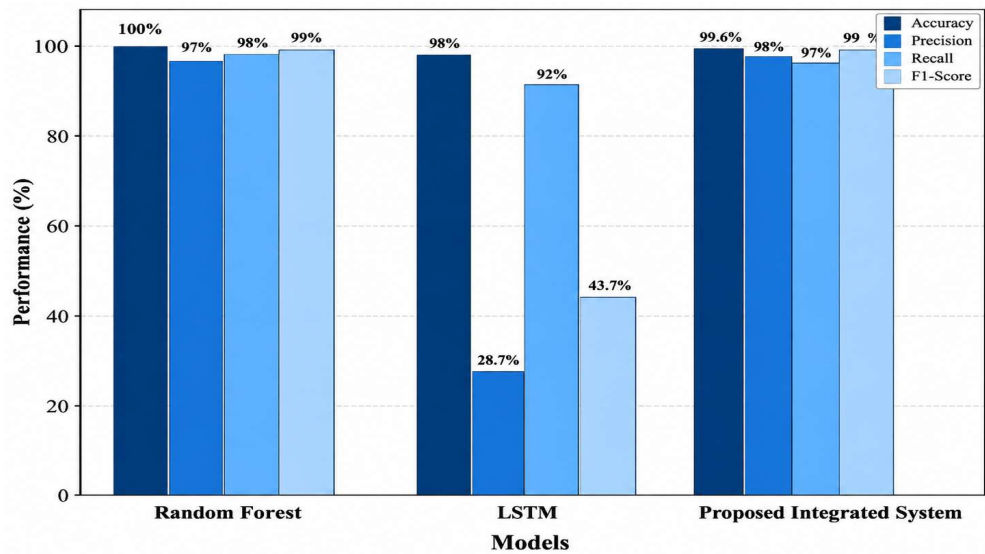


Fig. 5. Comparative performance of Random Forest, LSTM, and the proposed integrated predictive maintenance system

Table 2, the experiment results of anomaly-detection were very promising in terms of the ROC-AUC values of nearly 1.00 for Isolation Forest and nearly 0.83 for Autoencoder. The notable difference demonstrates that feature representation and dataset properties greatly affect anomaly-detection models' performance. The proposed remaining useful life prediction model based on LSTM showed RMSE of about 15-20 operation cycles on temporal prognosis task. This is a good evidence of its ability to detect degradation trends, even though its performance needs to be understood in the context of high computation cost and low explainability.

TABLE II: ANOMALY DETECTION AND TEMPORAL PREDICTION STATISTICS

Component Metric	Reported Outcome
Isolation Forest ROC-AUC	≈ 1.00
Autoencoder ROC-AUC	≈ 0.83
LSTM RUL Prediction RMSE	15-20 cycles

Overall, the findings are in favour of using an integrated framework as opposed to depending just on one prediction model. LSTM adds time-related prediction; Isolation Forest unsupervised identifies aberrant behaviour, and Random Forest is able to make very accurate and understandable condition predictions. Although security, scalability, privacy, and distributed data management remain to be important deployment challenges, this kind of integration is particularly relevant to heterogeneous IoT systems.

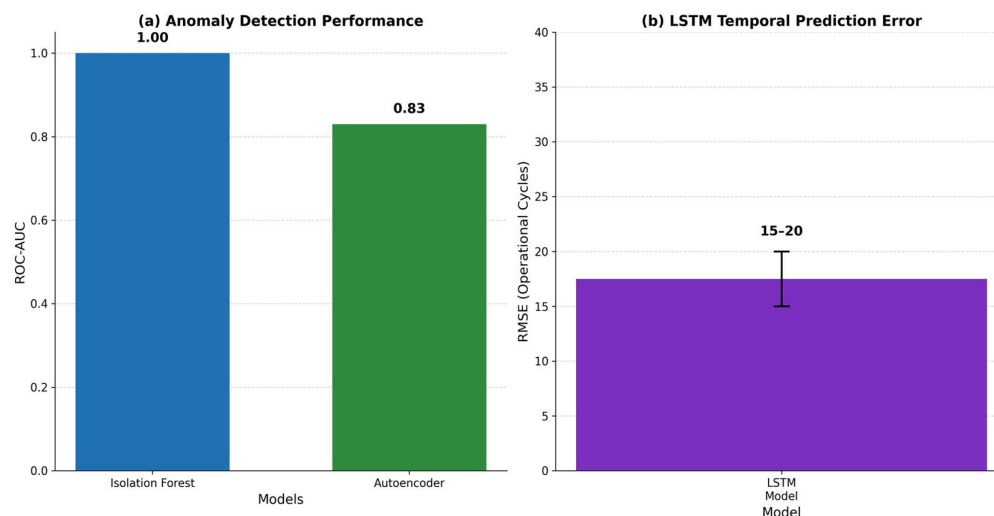


Fig. 6. Performance comparison of anomaly detection and temporal degradation prediction models

In figure 6, first panel compares two anomaly detection models by ROC-AUC score. Isolation Forest scores 1.00 which is a perfect score, meaning it separated normal from anomalous cases without error on this data. Autoencoder scores 0.83, still decent but clearly behind. Second panel shows the LSTM model's error when predicting how a system degrades over time, measured in RMSE (root mean squared error) in operational cycles. The bar sits at roughly 17.5, with an error bar spanning 15 to 20, which means the model's predictions are typically off by 15 to 20 operational cycles from the actual value.

6. CONCLUSION

This paper presented an IoT-based infrastructure maintenance system which facilitates a high level of urban resilience by detecting anomalies, using machine learning techniques to forecast the next time period, and continuously monitoring infrastructure. The proposed approach combines multiple and diverse sensor data to aid in the evaluation of the infrastructure state and prioritisation for maintenance. Based on the comparative analysis, some models are complementary that can be used to detect anomalies if they show abnormal operation behaviour, LSTM can be used to analyze the temporal degradation behavior, and ensemble learning is suitable for structured condition classification. The integrated framework offers a systematic approach to move from reactive maintenance to proactive decision-making. However, to make the proposed system realistically effective, the collection of reliable sensor information, accurate modelling, scalability and safety issues that arise at the integration of the system into various urban infrastructure items that need to be addressed with a lot of research and also the data collection will play a crucial role.

7. FUTURE SCOPE

The framework will be tested in the future with real life data from public infrastructures, water systems, highways and bridges. Additional technologies can also be collaborated with this work done such as digital twins for infrastructure modelling, federated learning for privacy-preserving distributed analytics and edge computing for low latency processing. To make the system more smooth and transparent maintenance recommendation systems can be modified with the help of artificial intelligence. In order to have a good surveillance system high order monitoring observations for the comprehensive infrastructure monitoring sophisticated technologies like computer vision, real-time geospatial data could be used.

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