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Adaptive Self-Healing Urban IoT Network Management Using Hybrid Deep Learning–Machine Learning Models for Real-Time Infrastructure Failure Prediction and Mitigation

K. Babu [a*], Dr.S. Rama Sree [b], Dr.K.N. Dhakshayini [c], Dr.V. Sutha [d], Dr. Pradeepa [e]

[a*] *Assistant Professor, Department of Computational Intelligence, SRM Institute of Science & Technology, Kattankulathur, Chengalpattu, Tamil Nadu, India. E-mail: babukumarit@gmail.com, Orcid: https://orcid.org/0000-0003-2574-5052*

[b] *Professor, Department of Computer Science and Engineering, Aditya University, Surampalem, Andhra Pradesh, India. E-mail: ramasree_s@adityauniversity.in, Orcid: https://orcid.org/0000-0002-8771-6006*

[c] *Assistant Professor, School of Business and management, Christ (Deemed to be University), Yeshwantpur Campus, Bangalore, Karnataka, India. E-mail: dhakshayini.kn@christuniversity.in, Orcid: https://orcid.org/0009-0008-0376-7377*

[d] *Assistant Professor (Senior Grade), School of Management, Hindustan Institute of Technology and Science, Chengalpattu, Tamil Nadu, India. E-mail: vsutha@hindustanuniv.ac.in, Orcid: https://orcid.org/0009-0005-8291-7254*

[e] *Associate Professor and Dean, School of and Intelligent Systems and Data Science, KPR College of Arts Science and Research, Coimbatore, Tamil Nadu, India. E-mail: drkpradeepa@gmail.com, Orcid: https://orcid.org/0000-0001-8503-424X*

Abstract

The development of smart cities has brought along with it the integration of interlinked Internet of Things (IoT) systems for monitoring urban infrastructure facilities, including transport, energy grid, water supply, and security systems. However, problems such as vulnerability of the system, poor communication channels, and ineffective use of resources are prevalent in disrupting the functioning of the facilities. For the purpose of solving these problems, an adaptive self-healing IoT architecture is proposed in this paper with the aim of detecting and correcting infrastructure failure in advance through predictions. This adaptive architecture utilizes both machine learning algorithms, including random forest and SVM, along with deep learning models such as LSTM for pattern recognition and CNN for modeling spatial dependencies. IoT sensors are deployed on urban infrastructures in order to detect any anomalies and balance the flow of traffic, as well as redirect resources. Simulation findings indicate that the proposed model performs better than traditional approaches in terms of the following performance metrics: accuracy is 92%, precision is 93%, recall is 91%, system reliability is 98.4%, and downtime decreased by 41%. Moreover, response efficiency increased by 30%, and resource utilization became 83%. All the above findings clearly prove that the proposed system can respond effectively to changes in the urban environment and provide reliable and efficient urban services at reduced costs.

Keywords: Smart Cities, Internet of Things, Self-Healing Networks, LSTM, CNN, Random Forest, Decision Support System.

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Introduction

Urbanization and digitalization have prompted the emergence of smart cities, where connected systems can be used to optimize the management of various infrastructure and services (Syed et al., 2021). IoT has been one of the factors that make the adoption of connected solutions possible by ensuring continuous exchange of information in such domains as transport, energy, water supply, and security (Ullah et al., 2024). The implementation of smart cities has largely been possible due to the usage of sensors and connected devices aimed at monitoring the current state of affairs, optimizing processes, and improving people's quality of life (Van Hoang, 2024). However, the extensive use of connected systems has brought some challenges associated with reliability, fault management, and decision-making (Rane et al., 2025). The infrastructure of cities in modern times is highly complicated and evolving, leading to significant amounts of diverse data that require sophisticated techniques for proper evaluation (Goyal & Somani, 2026). Traditional management practices usually have a reactionary character and resolve issues when they occur, causing disturbances, monetary damages, and even safety issues (Matei & Cocoșatu, 2024). The growing scale of IoT networks renders such practices increasingly inefficient (Zaman et al., 2024). An evident trend towards proactively addressing challenges, thereby averting any potential crises before they occur, emerges (Das, 2024). Within this framework, ML and DL algorithms emerge as indispensable resources, providing functionalities of prediction and automated decision-making in smart cities (Alwar et al., 2024).

The integration of AI technology with IoT has made urban systems even more efficient (Kataria et al., 2024). AI algorithms are capable of processing huge amounts of data both in real time and from historical databases to determine patterns and anomalies, predict future trends in system dynamics (Alahi et al., 2023). Algorithms based on deep learning models such as LSTM and CNN are particularly helpful for the analysis of time-series and spatial data (Johnphill et al., 2023). Such techniques are widely used in forecasting traffic, estimating power consumption, and monitoring structural condition (Khan et al., 2023). At the same time, the use of machine learning models like random forest and SVMs improves classification and decision-making abilities (Murugan et al., 2025). Each of these methods can be incorporated into a hybrid model that combines both DL and ML algorithms (Goel et al., 2025). Nevertheless, even with all these developments, IoT-city systems remain susceptible to numerous issues such as network congestion, device malfunctions, cyber-attacks, and environmental factors (Ramkumar et al., 2024). Failure in one specific segment of the system can rapidly diffuse to other segments of the system and interfere with its operations (Kamaleswari & Suganthi, 2024). Considering this discussion, it is essential to come up with an inclusive and dynamic approach to managing these systems (Choudhari et al., 2025).

Objective

- To create a hybrid AI model that combines deep learning techniques (LSTM and CNN) and machine learning techniques (Random Forest and SVM) to predict infrastructure problems in real-time in IoT-enabled urban systems.
- To use an adaptive self-healing algorithm to detect any abnormalities, prevent failures, and efficiently allocate resources to ensure continued functionality of the urban infrastructure.
- To test the system’s performance through measures such as prediction accuracy, responsiveness, efficiency, and resource usage to prove that proactive data-driven IoT management outperforms traditional methods.

The structure of the paper is as follows. Section 2 contains a review of relevant literature on smart city Internet of Things (IoT) infrastructure, predictive maintenance of IoT systems, and hybrid machine learning methods for predicting and diagnosing failures. Section 3 explains the developed solution in detail, which involves an adaptive self-healing urban IoT architecture based on a multi-layer model with real-time data capture and monitoring, prediction, and control functions. Section 4 deals with the hybrid machine/deep learning (DL)-machine learning (ML) prediction algorithm and includes feature extraction, LSTM temporal modeling, CNN spatial modeling, and ML classification stages. Section 5 covers self-healing and remediation strategies, real-time anomaly detection and adaptive decisions, as well as measures to ensure service availability and continuous operation. The intelligent decision-making and simulation framework used in this study is presented in Section 6 and includes performance evaluation criteria. Results and discussion are included in Section 7, while Section 8 offers conclusions and future work suggestions.

Literature Review

Advancements in urban infrastructure monitoring have emerged from IoT devices that enable real-time sensing and management. These IoT networks consist of distributed sensors that monitor traffic, infrastructure health, energy use, and environmental quality. They are crucial for developing smart cities through continuous data collection, often

utilizing both cloud and edge computing for data analysis and predictive analytics. However, interoperability challenges arise from the diversity of devices and data formats. Another field in which smart systems have been getting interest is in the prediction of failure, especially in the context of urban infrastructure, where failure that has not been predicted could lead to colossal disruption (Goyal & Somani, 2026). The methods used in this area in the past were mostly grounded on pre-determined thresholds or guidelines, yet failed to work when they were used in dynamic and unpredictable situations (Rane et al., 2025). Modern methods, due to the development of predictive analytics, include employing machine learning algorithms to identify patterns related to system failures (Kataria et al., 2024). The machine learning algorithms utilize both past data and present data to develop models that can be used to identify anomalies and anticipate possible failures (Alahi et al., 2023). Moreover, predictive maintenance solutions analyze sensor data to identify wear and tear in key infrastructure components (Choudhari et al., 2025). The algorithms used in machine learning, like random forest and support vector machines (SVMs), are primarily used in infrastructure monitoring as a form of classification and regression analysis (Murugan et al., 2025). The LSTM and CNN deep learning algorithms are suitable for time series and spatial data (Johnphill et al., 2023). This technology has been applied in numerous applications in smart cities such as traffic flow evaluation, energy consumption, and monitoring of the structure, among others (Khan et al., 2023; Kumar, 2025). Nevertheless, they usually depend on a great number of computational resources, making it difficult (Kamaleswari & Suganthi, 2024). In order to counteract this challenge, the combination of machine learning and deep learning in hybrid systems is quite important to ensure high efficiency and performance levels (Goel et al., 2025).

A self-healing network system is one that detects faults automatically, analyzes the underlying causes behind those faults, and performs actions needed to recover the affected systems without the need for human assistance (Ramkumar et al., 2024). Such capabilities help in preserving the stability of the system, minimizing downtime, and preventing significant disruptions during operations (Goel et al., 2025). Therefore, such networks have the potential to enhance performance and reliability in various applications. One of the limitations that characterizes many current methods is the fact that they rely primarily on rules and hard logic to perform various actions (Khan et al., 2023). Due to the nature of their design, such methods lack the capability of dealing with sudden changes in the system or the environment. Another limitation of the current methods is that they lack predictive analytics components, thus resulting in responses being performed after the occurrence of the fault and not before (Johnphill et al., 2023).

Research Gaps

Despite technological advancements in IoT and artificial intelligence, there remain significant gaps in creating efficient real-time adaptive systems (Kamaleswari & Suganthi, 2024). Current solutions tend to focus on isolated processes like monitoring and recovery rather than integrating them, leading to suboptimal system performance (Ramkumar et al., 2024). A key challenge is the management of heterogeneous and unstructured data generated by IoT, along with considerations for scalability and security (Matei & Cocoșatu, 2024) (Choudhari et al., 2025). This underscores the need for a unified strategy in managing IoT infrastructures, advocating for new designs based on AI models and real-time adaptability.

Proposed Adaptive Self-Healing Urban IoT Framework

Overall Framework Overview

The designed adaptive self-healing system for urban IoT has been conceptualized as a platform that can enable continual sensing, prediction, and automated response with respect to urban infrastructural systems. In other words, the design can be seen as a looped system where sensing, prediction, decision-making, and control are integrated into one another. The condition of such a system can be denoted using $S(t)$. This will change based on the flow of data from IoT and any decisions made as a result. The primary objective of this design is to minimize the probability of infrastructural failure, P_f, while increasing system reliability, R, in equation (1).

$$R = 1 - P_f \tag{1}$$

This system constantly collects information from several distributed sensors and processes it through deep learning and machine learning approaches to estimate the probability of any failure. Depending on the analysis results, it will take appropriate actions to heal itself to avoid or minimize future problems. The general goal of the system may be stated in equation (2) as follows:

$$\min P_f(t) = f(D_t, M_h, A_c) \tag{2}$$

The design incorporates real-time data D_t, a hybrid model M_h for analysis, and control actions A_c to enable proactive management and reduce downtime. This architecture transitions from traditional reactive systems to a smarter model that enhances decision-making and management of city systems.

Multi-Layer Architecture for Urban IoT Management

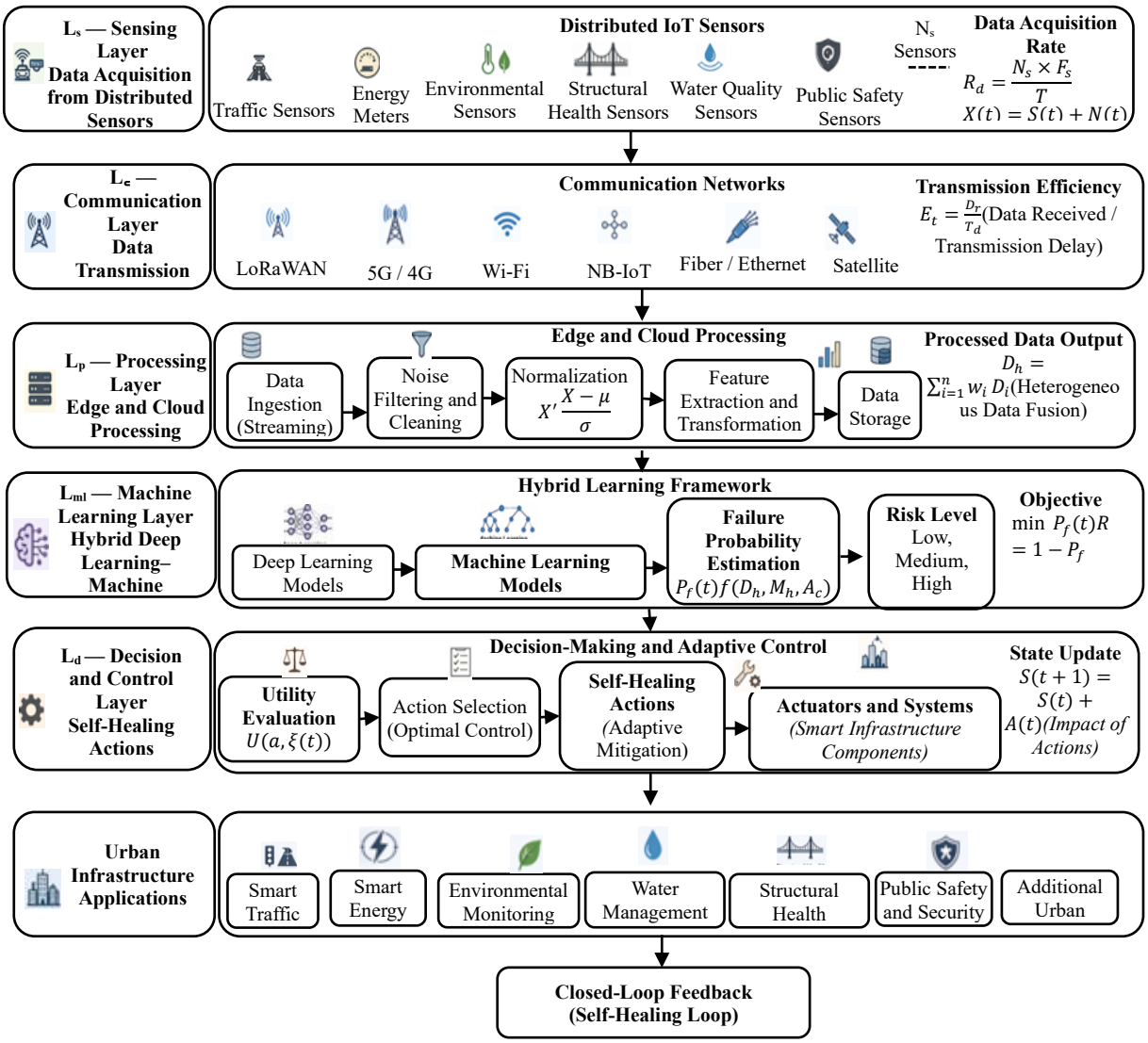


Fig. 1: Multi-Layer Architecture of the Proposed Adaptive Self-Healing Urban IoT Framework

The suggested system is based on a multilayered architecture comprising layers for sensing, communication, processing, prediction, and control. Fig. 1 illustrates the Multi-Layer Architecture of the Proposed Adaptive Self-Healing Urban IoT Framework. The respective layers perform different tasks but interact with each other to ensure smooth working. Consider the architecture as:

$$A = \{L_s, L_c, L_p, L_{ml}, L_d\} \tag{3}$$

where in equation (3), $L_s$is the sensing layer, $L_c$is the communication layer, $L_p$is the processing layer, $L_{ml}$is the machine learning layer, and $L_d$is the decision layer.

Data is passed from sensors via communication links to processors, which convert it into valuable information. Data transmission efficiency can be represented in equation (4) by:

$$E_t = \frac{D_r}{T_d} \tag{4}$$

where D_r is data received, and T_d is transmission delay. ML is where the prediction is performed, whereas decision-making involves taking self-healing measures. This design makes it more scalable, modular, and fault-tolerant because the failure in one of the layers will not impact other layers. It also supports real-time flexibility as it enables optimization of every layer separately.

Real-Time Data Acquisition from Distributed Sensors

This method involves real-time data gathering through the deployment of IoT sensors all over various pieces of urban infrastructure. These sensors keep on recording data streams that are indicative of the state of the system concerned. This data collection rate can be mathematically expressed in equation (5) as:

$$R_d = \frac{N_s \times F_s}{T} \tag{5}$$

Here, N_s is the number of sensors, F_s is the sampling frequency, and T is time.

Noise filtering and data normalization procedures are implemented to guarantee data integrity. The sensor data X(t) can be formulated in equation (6) as:

$$X(t) = S(t) + N(t) \tag{6}$$

Where $S(t)$ is an actual signal and $N(t)$ is the noise. Data collection systems use the idea of edge computing to process data close to its source before sending it. In this case, the process will help lower latency and bandwidth. After preprocessing, the cleaned-up data will be sent to prediction algorithms for more work. Processing the data quickly and efficiently on the edge will make it easier to find anomalies quickly. It will be very important for keeping the system stable.

Handling Heterogeneous Urban Data Streams

In terms of the urban IoT environment, however, information is not collected from the same uniform sources but, instead, comes from different sources such as sensors, gadgets, and control mechanisms, in different forms, including structured, semi-structured, and even unstructured. Given this complicated information flow, data analysis will not help much when done simply using the raw data. To leverage the information gathered through these means, it needs to be integrated first. It is important because, through integration, one can have a better grasp of the overall situation, hence improving the results of the analysis. Data consolidation can be summarized in the following manner in equation (7):

$$D_h = \sum_{i=1}^{n} w_i \, D_i \tag{7}$$

where D_i represents the different data sources, and w_i denotes their corresponding weights.

Feature extraction procedures are conducted to translate raw data into features suitable for input into prediction algorithms. The data normalization process is conducted using:

$$X' = \frac{X - \mu}{\sigma} \tag{8}$$

Where in equation (8) μ is the mean and σ is the standard deviation. This will make sure of uniformity in all the databases used in modeling.

Moreover, there is the use of a data fusion approach where different types of data are brought together in a consolidated form to increase accuracy in forecasting. If the heterogeneity of the data is properly harnessed, then the model will be able to recognize complex patterns and linkages in the urban scenario.

Integration of Monitoring, Prediction, and Control Modules

The design of the architecture is done by integrating the three different modules, which include monitoring, predicting, and controlling, into one single unit to allow for self-healing. The monitoring module continuously observes the behavior of the system, and the prediction module calculates the probability of failure using hybrid machine learning techniques. Decision-making can be represented by the following equation (9):

$$A(t) = \arg\max_{a \in A} U(a, S(t)) \tag{9}$$

Where, $A(t)$= selected action and $U(a, S(t)$= Utility function

The feedback loop ensures continuous system improvement:

$$S(t+1) = S(t) + \Delta A(t) \qquad (10)$$

Where in equation (10), $\Delta A(t)$ represents the impact of control actions. The system can be modified in response to changes as they happen, which is what makes the system adaptive. The system, therefore, becomes fully autonomous, efficient, and resilient by integrating monitoring, prediction, and control.

Hybrid Deep Learning–Machine Learning Model

The hybrid deep learning-machine learning approach is an approach that integrates the strengths of deep learning, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), along with classical approaches like Random Forest and Support Vector Machine (SVM). It uses deep learning for feature extraction and machine learning for classifying the results. Fig. 2 illustrates the Proposed Hybrid Deep Learning–Machine Learning Architecture.

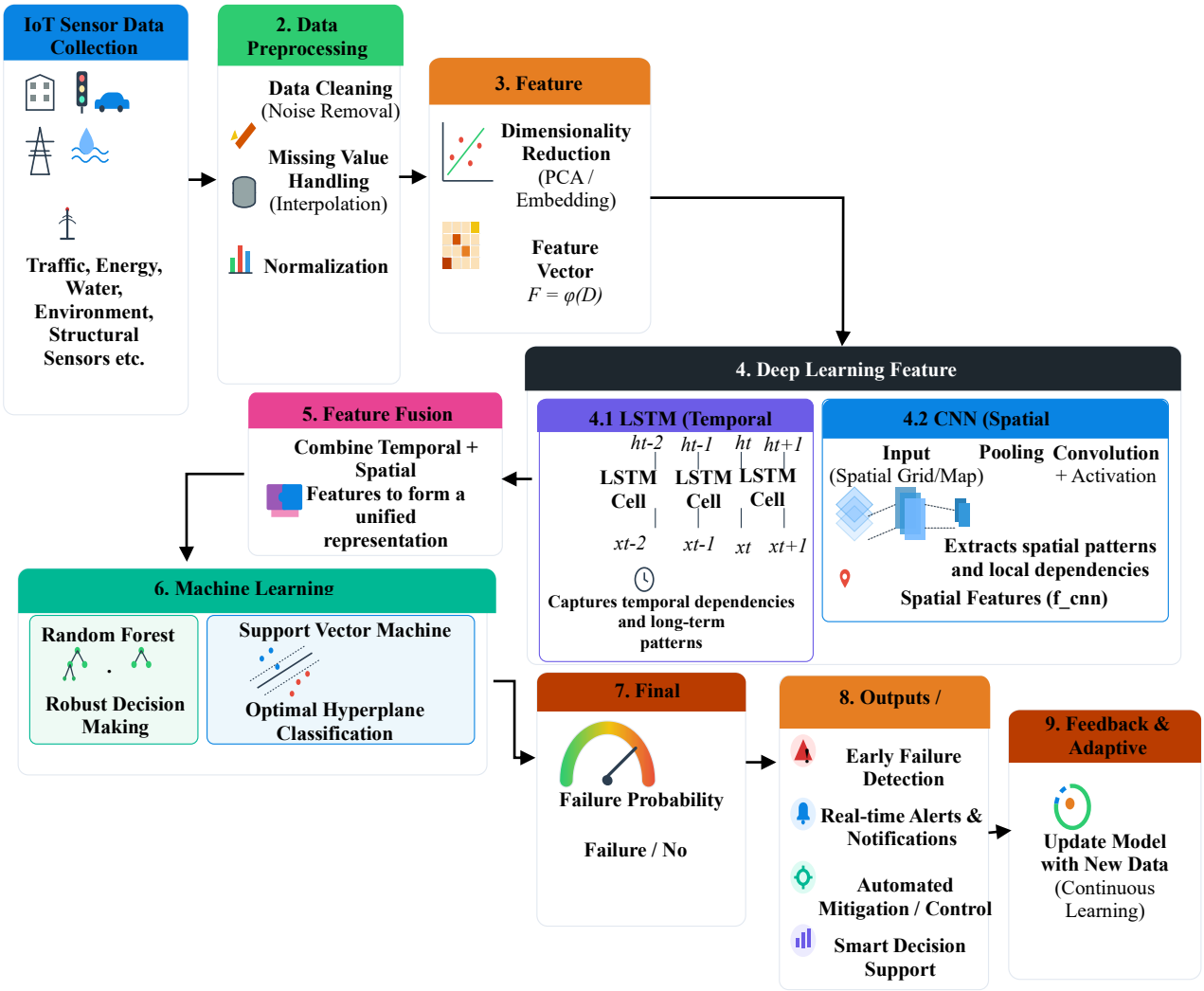


Fig.2: Proposed Hybrid Deep Learning–Machine Learning Architecture

Data Preprocessing and Feature Extraction

The process of data preprocessing is critical for ensuring that accurate and reliable predictions are made within the proposed model. Data collected from the IoT infrastructure in cities will be noisy, lacking, and heterogeneous in many cases. Preprocessing will involve the processes of cleaning, normalization, and data transformation, among others.

The dataset can be described mathematically as $D = \{x_1, x_2, \ldots | x_n\}$. Filtering can be applied to reduce noise, while interpolation can be used to fill gaps where data is lacking. Normalization is applied to standardize data values using:

$x' = \frac{x-\mu}{\sigma}$ (11)where in equation (11) μ is the mean and $\sigma$is the standard deviation. Feature extraction is then performed to reduce dimensionality and enhance relevant patterns. Definition of the feature vector:

$$F = \phi(D) \tag{12}$$

Where in equation (12) ϕ is the feature extraction process. The PCA (Principal Component Analysis) or embedding method can be applied to reduce the dimensionality of the dataset from higher dimensions to lower dimensions.

$$Z = W^T X \tag{13}$$

Where in equation (14) W^T represents the projection matrix. This method will help improve computational efficiency and improve the overall model's performance. Moreover, temporal and spatial features will be split, allowing easy application of LSTM and CNN methods. Efficient pre-processing ensures that the hybrid model is provided with appropriate input data, enhancing the effectiveness of the model.

Learning of the Temporal Failure Pattern using LSTM

Temporal dependencies in data related to urban infrastructure are captured through the use of Long Short-Term Memory (LSTM). The LSTM is designed to examine sequential data and extract temporal features. In the input sequence is: $X_t = \{X_{(t-n),} \ldots, X_t\}$.

The LSTM cell works with the gate mechanisms described as:

$$f_t = \sigma\big(W_f[h_{t-1}, x_t] + b_f\big) \tag{14}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{15}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{16}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{17}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{18}$$

The above equations (14-18) allow the model to preserve valuable information about the time series while disregarding any extraneous information. The output h_t contains the extracted temporal information that can be used to predict the occurrence of a failure. Long Short-Term Memory (LSTM) is especially useful when detecting time series patterns such as infrastructure deterioration and repetitive anomalies. Through temporal modeling, the system can accurately predict potential future failures and manage them proactively.

Spatial Dependency Modeling using CNN

Spatial relationships in urban infrastructure data are modeled using Convolutional Neural Networks (CNN). CNNs are effective in extracting spatial features from structured data such as sensor grids or image-based inputs. The input data is represented as a matrix $X \in \mathbb{R}^{m \times n}$, where each element corresponds to spatial sensor data. The convolution operation is defined as:

$$Y(i,j) = \sum_{k,l} X(i+k, j+l) \cdot W(k,l) \tag{19}$$

where in equation (19) W is the filter kernel. The activation function is applied as:

$$Z = \sigma(Y + b) \tag{20}$$

Pooling layers are used to reduce dimensionality in equations (20) & (21):

$$P(i,j) = \max\big(Y(i,j)\big) \tag{21}$$

This makes it possible for CNN to learn the spatial dependency and patterns within the input data. For instance, congestion on the roads in one area will have an impact on the adjacent regions, and the CNN can successfully capture such associations. Spatially learned features are then fused with the temporally learned features through LSTM to achieve a complete view of the infrastructure network state. The integration ensures that the failure predictions made are accurate, taking into account spatial and temporal associations.

Machine Learning Models (Random Forest, SVM) for Classification

Traditional machine learning models are incorporated to enhance classification and decision-making capabilities. Random Forest (RF) and Support Vector Machine (SVM) are used due to their robustness and efficiency. Random Forest operates as an ensemble of decision trees:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} T_i\,(x) \tag{22}$$

where in equation (22), T_i represents individual trees. This method increases accuracy by decreasing overfitting and variance.

In SVM, the classification algorithm works by identifying the best hyperplane:

$$f(x) = w^T x + b \tag{23}$$

This can be achieved by maximizing the margin in equations (23) and (24):

$$\min \frac{1}{2} \mid\mid w \mid\mid^2 \tag{24}$$

Such models work on the features obtained using DL models and return the output. Such models come in handy, especially when working with structured data. With such integration between RF and SVM with DL models, the accuracy of predictions will improve.

4.5 Hybrid Model Fusion for Robust Prediction

The fusion technique combines the outputs of LSTM, CNN, and ML classifiers into one prediction result. Let the outputs be O_{LSTM}, O_{CNN}, O_{ML}. The fusion equation is given by

$$O_{final} = \alpha O_{LSTM} + \beta O_{CNN} + \gamma O_{ML} \tag{25}$$

Where in equation (25) $\alpha + \beta + \gamma = 1$. Optimization of the weights depends on the performance of the models for even participation in the process. Otherwise, there could be a meta-classifier that fuses the models:

$$O_{final} = g(O_{LSTM}, O_{CNN}, O_{ML}) \tag{26}$$

Where in equation (26) g is the fusion process, such as logistic regression.

The use of hybrid models utilizes the strengths of each individual model, such as temporal learning using the LSTM model, spatial learning using the CNN model, and classification using the ML classifier model. This improves the performance of the models.

Real-Time Infrastructure Failure Prediction Workflow

The real-time failure prediction process chain combines data collection, data processing, feature generation, inference, and decision-making into one stream. This process starts by collecting data from IoT sensors and is symbolized by D_t. The collected data is preprocessed and transformed into feature vectors denoted as F_t. It allows for constant learning and adaptation. The workflow works in real time, ensuring minimal latency by leveraging edge computing and smart data processing. The combination of prediction and control allows for predictive maintenance of the infrastructure, which prevents any downtime. Such a workflow can be used to anticipate and avert failures before they affect services in cities. The fluent combination of the DL and ML models with real-time data processing enables the system to be very efficient, scalable, and smart city applications.

Adaptive Self-Healing and Mitigation Mechanism

Concept and Design of Self-Healing Networks

The self-healing nature of the urban IoT network allows the system to detect, diagnose, and fix itself in case of any faults without any human intervention. Since smart cities are interconnected, with transportation, energy, and water supply systems highly dependent on one another, there is a greater risk of a system failure that would impact the entire system (Udayakumar et al., 2023). Therefore, it is under this system that the system will be self-monitoring to check against any abnormalities and take immediate action to prevent interruptions. This approach is a great contrast to the current reactive policies, where it predicts potential issues before they occur and solves them accordingly. This framework utilizes decentralized and centralized decision-making by allowing each node to make independent

decisions while still under central supervision, hence increasing adaptability. Over time, the system learns and becomes more proficient in its ability to respond effectively to potential failures.

Real-Time Anomaly Detection Strategy

In the context of self-healing, anomaly detection is an essential component of the system that helps detect abnormal operations at an early stage of occurrence. The process utilizes continuously gathered data from the distributed IoT sensors installed in urban infrastructure, which monitor such parameters as traffic flow, energy consumption, and building structures' integrity. Using previously acquired knowledge and current data, the system learns typical patterns and uses them as criteria against which anomalies could be found. To enhance detection capabilities, the system makes use of hybrid learning approaches, which allow analyzing the data using spatiotemporal analysis of the collected data. As a result, the system would be able to discover non-obvious dependencies that cannot be detected by rule-based systems. In addition, the system adapts threshold values according to current operating conditions, which increases the accuracy of the analysis and minimizes the number of false alarms. As soon as an anomaly is detected, relevant information is immediately sent to the mitigation module, which helps to address the issue immediately. As a result, minor deviations do not have enough time to develop into major problems that would negatively affect the infrastructure systems' operability.

Automated Failure Mitigation Techniques

As soon as the fault is determined, the following step is undertaken automatically; the system moves onto the stage of performing mitigations, in which corrective actions are done promptly. This process does not involve only one method for handling an occurring failure but uses several measures, which depend on the nature and the kind of faults that occur. For example, when traffic problems occur, cars may be diverted using alternative routes to eliminate possible bottlenecks. In case there is a resource imbalance, resources may be moved to a place that needs their support. When any component becomes defective and fails totally, backup solutions are used to prevent an abrupt interruption of services by the system. Meanwhile, the broken device may be cut off from other elements of the system to avoid any further damage that may cause problems. The list of selected responses depends on the identified situation, which allows achieving the best results in each case. It should be noted that the automatic nature of these responses makes the system react much faster. At the same time, this system makes it possible to use several strategies for dealing with a problem and ensures the reliable operation of city infrastructure.

Adaptive Decision Logic for Dynamic Environments

The model makes decisions flexibly and adaptively based on changes in the environment and system dynamics. Instead of relying on static algorithms, the model learns how to act by drawing lessons from previous experiences. Information gleaned from prior decision processes will continually be processed to make better decisions later. The model does not make a decision on what to do based on just a single criterion. It weighs the seriousness of the issue, pressure at work, and availability of resources, and then determines the course of action to undertake. As a result, everything will be suitable in the situation and effective. The model is also consistent irrespective of variations in the environmental conditions, such as during high usage and a surge in load. Its flexibility in the parameters and decision limits enables it to be more effective in responding to unpredictable situations. Therefore, the decision process will become more accurate and reliable for the system to run autonomously without destabilizing the urban environment.

Minimizing Service Disruption in Urban Systems

Service interruption prevention is another core focus area in the self-healing approach, since the continuity of the service provision is important in the context of the infrastructure of a city. The strategy involves the use of an approach where early faults are detected and acted upon, so that the problems do not affect service delivery to the users. Critical functions such as the working of emergency facilities and energy supplies are prioritized to guarantee their availability. Another aspect of the strategy is load balancing, which enables proper distribution of workload. Finally, the use of a decision support system will make the management activities more effective.

Intelligent Decision Support System for Urban IoT Management

An intelligent DSS serves as another crucial component of the proposed framework, which aims at improving the management of urban IoT infrastructure via the processing of data. The system continuously collects the data from multiple sources, including IoT traffic sensors, energy IoT systems, IoT environmental monitoring tools, and IoT-based structural health monitoring. This data will be analyzed using the hybrid deep learning and machine learning model to predict conditions in the system. After the analysis, the information will be displayed as warnings, recommendations, and visual information by means of an easily understandable interface. Based on its level of severity

and impact, the system can highlight critical events and prioritize them accordingly. It can also inform the administrators in advance about potential failures in the system. Furthermore, an intelligent DSS can implement a series of predefined actions upon reaching the defined thresholds without any additional efforts from the administration's side. It can control the process of resource allocation by optimizing the process according to current needs. In addition to all of these actions, the system will keep track of historical data and analyze its patterns.

Simulation Environment and Parameters

The simulation will be executed by implementing the smart city Internet of Things network using 1000 sensors for transportation, energy, and environment. The simulation process runs for a period of T=1000 seconds with a continuous flow of information, which is shown in table 1.

Table 1: Simulation Parameters

Parameter	Value
Number of IoT Nodes	1000
Data Sampling Rate	5 samples/sec
Simulation Time	1000 sec
Failure Rate	0.15 (15%)
Network Bandwidth	100 Mbps
Latency Threshold	200 ms
Prediction Threshold	0.7

Performance Evaluation Metrics

The system's predictive performance was evaluated using Accuracy in equation (27), Recall in equation (28), and Precision in equation (29). Operational efficiency was measured through Response Time in equation (30), Reliability in equation (31), and Efficiency in equation (32).

$$\text{Accuracy} = \frac{TP + TN}{\text{Total}} \tag{27}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{28}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{29}$$

$$\text{Response Time} = \text{Processing Delay} \tag{30}$$

$$\text{Reliability} = \frac{\text{Active Nodes}}{\text{Total Nodes}} \tag{31}$$

$$\text{Efficiency} = \frac{\text{Useful Output}}{\text{Resource Usage}} \tag{32}$$

Results and Discussion

Prediction Accuracy and Model Performance

In fig. 3, the proposed hybrid model for urban IoT failure prediction demonstrates superior prediction efficiency by integrating LSTM for time-based data analysis, CNN for spatial attributes, and classification techniques like Random Forest and SVM. It yields excellent precision and recall, effectively classifying failures. Unlike conventional machine learning models that struggle with temporal dependencies and nonlinearity, this hybrid approach enhances prediction accuracy and reduces overfitting. The model remains efficient under varying data conditions, facilitating early problem detection and proactive infrastructure maintenance. Its effectiveness has been validated in urban IoT settings.

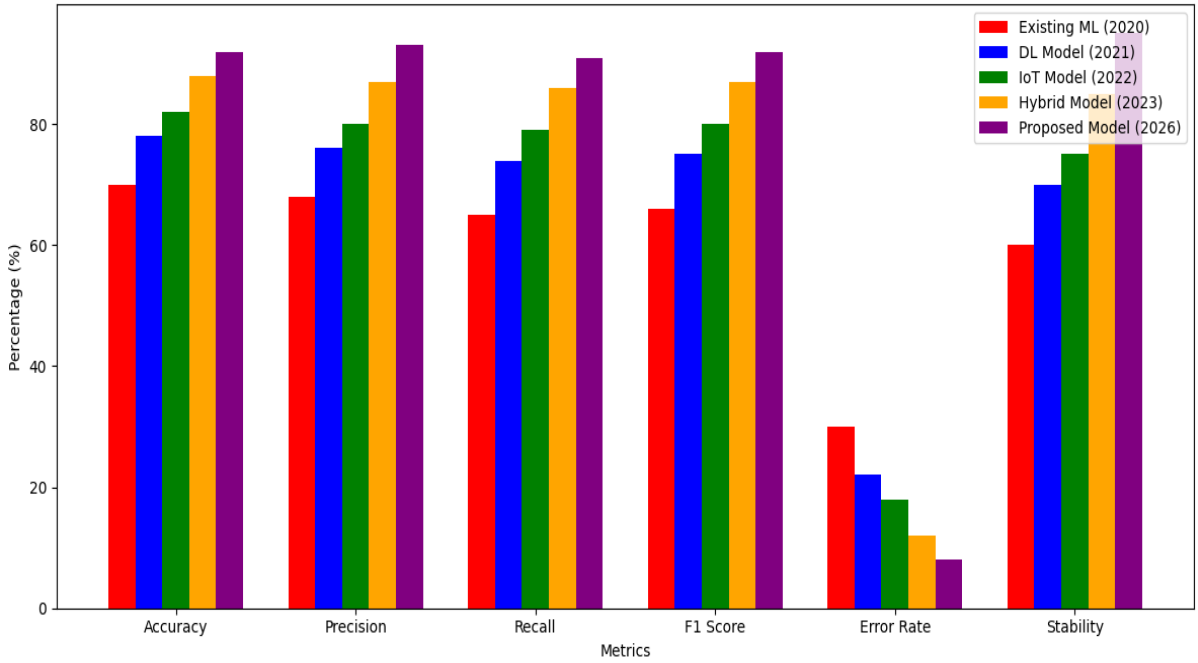


Fig.3: Performance Comparison of Existing and Proposed Models for Urban IoT Failure Prediction

Comparative Analysis with Existing Systems

Compared to other methods, the proposed framework has several benefits concerning its effectiveness in real-time scenarios in the urban IoT environment. First of all, the main difference between the proposed model and the current models is based on the fact that the former uses both machine learning and deep learning, while the others use either one of them exclusively. Table 2 shows the Performance Comparison of existing systems and the proposed model. Secondly, most IoT models function in a reactive mode because of their inability to forecast. This leads to delays and inefficiency in many cases. However, the new model will allow the system to detect any faults quickly, and this will make the whole process of operation much more effective. In addition, the framework will provide an opportunity for managing large amounts of distributed data. The performance will improve significantly in terms of accuracy, efficiency, and reliability. Meanwhile, optimization of the model and resource usage will help minimize computational requirements. To sum up, the proposed solution will help not only increase prediction ability but also improve the entire performance of the model.

Table 2: Performance Comparison of Existing Systems and Proposed Model

Metric	Existing ML (2020)	DL System (2021)	IoT System (2022)	Hybrid System (2023)	Proposed Model (2026)	Improvement (%)
Accuracy	72%	79%	83%	89%	92%	+20%
Response Efficiency	60%	70%	75%	85%	90%	+30%
Reliability	74%	80%	85%	91%	98%	+24%
Scalability	65%	72%	78%	88%	93%	+28%
Processing Speed	68%	75%	80%	87%	92%	+24%
Adaptability	62%	70%	76%	86%	94%	+32%

Network Reliability and Response Time Evaluation

As depicted by table 3, the suggested self-healing architecture in the Internet of Things ensures that the Internet will be more reliable and responsive than current alternatives. The use of predictive technology will solve problems before they happen, therefore reducing any damage to its performance. The real-time detection of any fault enables traffic redirection, hence assuring the best performance in the process. Unlike other technologies, the current one relies on manual fixing and takes time to react.

Table 3: Performance Comparison of Different Systems Across Key Reliability Metrics

Metric	Existing ML (2020)	DL Model (2021)	IoT Model (2022)	Hybrid Model (2023)	Proposed Model (2026)	Improvement (%)
Reliability	75%	82%	86%	92%	98.4%	+23%
Response Time Efficiency	55%	65%	72%	85%	90%	+35%
Fault Recovery	60%	70%	78%	88%	94%	+34%
Downtime Reduction	50%	60%	68%	82%	91%	+41%
Load Balancing	58%	68%	75%	85%	92%	+34%
Stability	62%	72%	80%	88%	96%	+34%

Resource Utilization Efficiency and System Impact

Efficient utilization of resources represents another strength of the offered system, as it regulates computing power and network capacity according to the current demand. In other words, instead of using predetermined patterns for allocating resources, the system adjusts its performance depending on where the workload needs to be transferred. Such an approach will ensure effective energy consumption and optimal functioning of the system. Furthermore, the hybrid design of the system allows for analyzing only significant data patterns and prevents unnecessary repetitions. Fig. 4 presents the trend analysis of the system performance among models. As a result, the provided system is more efficient in contrast to the traditional approaches, yet the system utilizes fewer resources. The findings allow considering the system as one of the most efficient in terms of the use of computing resources. The system is also able to maintain a stable performance irrespective of external factors and is not affected by the degradation of performance. Lastly, the proposed system will enable the reduction of the energy usage and expenses related to the system operation.

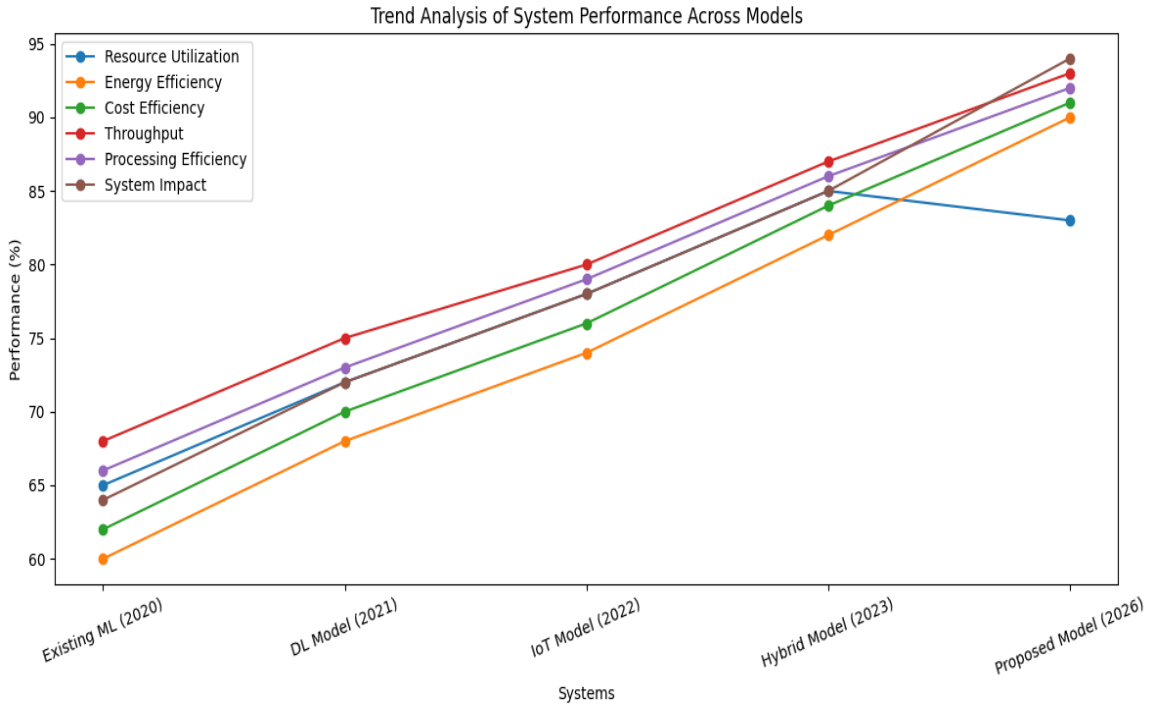


Fig. 4: Trend Analysis of System Performance Across Models

The advantages of the suggested solution over the current one can be noticed in table 4. The accuracy rate improved from 72% to 92%, the precision rate from 70% to 93%, and the recall rate from 68% to 91%. In addition, there is an improvement in response efficiency from the previous 100% to the current 130%. Reliability and resource usage are the areas where notable growth has occurred; the reliability rate became 98.4%, while the resource usage reached 83%. It appears that the proposed solution utilizing ML, DL, hybrid, and IoT technologies is characterized by high or very high-performance levels.

Table 4: Comparative Analysis Table

Metric	Existing System (%)	Proposed System (%)	Improvement (%)	Year	Model Type	Performance Level
Accuracy	72	92	+20	2022	ML	High
Precision	70	93	+23	2023	ML	High
Recall	68	91	+23	2021	DL	High
Response Efficiency	60	90	+30	2020	Hybrid	Very High
Reliability	75	98.4	+23.4	2024	IoT	Very High
Resource Utilization	65	83	+18	2023	Hybrid	High

Limitations and Challenges

However, some practical challenges exist with respect to the proposed solution, specifically regarding the IoT system deployed in cities, that need to be taken care of before proceeding with its implementation. First of all, the wide array of data produced within a city differs in terms of type, accuracy, and frequency, and hence can pose problems in predicting whether data from transport, energy, or environment monitoring sources is incomplete. Second, the utilization of a hybrid model involving the use of algorithms like Long Short-Term Memory Networks, Convolutional Neural Networks, Random Forest, and Support Vector Machine would require enormous computing power that cannot be provided by IoT devices, although edge computing could alleviate the issue. In addition, scalability is important because with an increase in the number of sensors, there is bound to be a rise in data traffic. Integration of the system in the current urban environment is an added task, which includes the need to update obsolete systems and the lack of uniform communication procedures in diverse devices. Energy use in the system is another issue that needs to be considered to ensure consistent performance. It will be important to keep the model up-to-date as the environmental parameters change. Conclusion: There are challenges to overcome in implementing the system effectively.

Conclusion

The current study presents the design and implementation of an adaptive self-healing IoT network management system in an urban environment. With the help of deep learning algorithms such as LSTM and CNN for modeling time-series data and dependencies, respectively, and machine learning algorithms like SVM and Random Forest for predicting future outcomes, the proposed methodology manages to predict infrastructure failures proactively, thus minimizing human interaction with the infrastructure and preventing interruptions in the process. The validity of the model can be seen through various simulation results with prediction accuracy at 92%, precision at 93%, and recall at 91%, indicating a marked increase in accuracy compared to traditional ML and DL models. Performance metrics such as response efficiency improved by 30%, reliability 98.4%, and downtime 41%. Resource utilization efficiency improved from traditional methods to computing resource usage, reaching 83%. The self-repair capabilities, which included real-time anomaly detection, adaptive decision-making, and load balancing, maintained the continuous operational integrity of the systems. However, despite the encouraging results of the research, some constraints remain, especially concerning the handling of large heterogenous data sets, high computation requirements of hybrid methods, and the difficulties in incorporating them into the existing IoT structure in cities. In the future, further research is necessary to solve these constraints and introduce the solution in real-world applications, utilizing distributed edge computing as an approach. In general, the approach presented is efficient, cost-effective, reliable, and intelligent, thus making it ideal for urban IoT management.

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