Rover Publications
United International Journal of Engineering and Sciences (UIJES)
An International Peer-Reviewed (Refereed)Engineering and Science Journal
Impact Factor:8.075(SJIF) Vol-5, Issue- 4,(December);2025 ISSN:2582-5887 www.uijes.com

Smart Cities Powered by the Internet of Things: Resource Allocation with Precision Using Machine Learning Assessment Metrics

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Abstract
The rapid penetration of Internet of Things (IoT) devices in smart cities poses new and unique challenges in resource allocation and timely decision-making at both the computational and communication levels. This paper describes a multi-precision machine learning framework for dynamic resource allocation in smart cities with IoT support. In the context of a resource-aware smart city, we simulated a smart city scenario with specific resource constraints and worked with synthetic IoT workload data to evaluate five widely used classification techniques: Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Naive Bayes (NB), and Decision Tree (DT). Every model is evaluated using a collection of metrics: model accuracy, precision, recall, F1 score, area under the ROC curve (AUC), and the Kolmogorov–Smirnov (KS) statistic. The results indicate SVM model outperforms the rest of the models in classification and precision recall compromise. This strengthens the reliability of SVM traffic and energy load balancing forecasts. The framework provides integrated statistical and visual model performance evaluations through the use of confusion matrices, bar graphs, pie charts, and histograms. The results demonstrate the importance of model selection and multi-criteria optimization for resource-aware IoT smart city data using machine learning.

Keywords: Smart Cities, Internet of Things (IoT), Resource Allocation , Machine Learning, Model Evaluation Metrics , Precision Aware Systems, Support Vector Machine, Federated Learning, Smart Infrastructure Optimization, Edge Computing

1.Introduction

Smart cities are taking off thanks to a surge of Internet of Things (IoT) devices that keep sending streams of data. This data pours in from smart traffic lights, power grids, air quality sensors, and public safety cameras, among other places[1]. Collectively, these tiny sensors and actuators create a data deluge that smarter city planners and decision-makers must turn into actions. Yet, the urban patterns they must respond to change faster than ever, making it crucial that the city's computing power can keep up. The tricky part is spreading out that power in a way that is smart, fast, and energy-friendly—especially when not all sensors, cells, and gateways speak the same "language." Relying solely on giant data centers in the cloud is no longer an option. Sending massive files from hundreds of crossroads cameras or grid

nodes to a distant server can slow the system and gobble up bandwidth. More importantly, it creates security holes that can let sensitive data slip[2]. To tackle this, engineers are increasingly deploying edge computing and federated learning. These architectures move the work closer to where the data is created—on the curb, the lamp post, or the rooftop. The result is quicker responses, stronger privacy, and smarter local choices. The catch? We still need smart algorithms that can juggle processors, radios, and batteries in real time, ensuring no part of the city dims, delays, or drifts off-course. Machine In This Advanced Study, We Explored Precision Planning Resource Allocation In The Context Of IoT, With A Machine Learning Approach.

We apply multiple classical machine learning models in the context of a Federated Learning (FL) simulation, focusing on the FL model adapted to IoT devices and smart cities paradigm[3].

We study the performance of five classifiers: Support Vector Machine, Random Forest, Logistic Regression, Naive Bayes, and Decision Tree using a wide range of evaluation metrics:13 accuracy, precision, recall, F1 score, AUC, and the Kolmogorov–Smirnov (KS) statistic[4]. Out of the five classifiers considered, SVM was the best for making high precision resource allocation decision due to its high classifying accuracy and model strength in numerous simulated workloads.

The implementation of simulated Federated Learning models provides a meaningful explanation of the working structure, especially in smart city models[5]. The locality of edge nodes allows for privacy-conscious model training at the edge and the aggregate at the cloud level provides for privacy preserving model aggregation. Explaining the infrastructure in these terms allows for a smart city model to adapt, scale, and learn from the constantly changing decentralized heterogeneous IoT data. Our methods address privacy concerns and adapt to the ever-evolving data[6]. The Inverse Focus Model of urban critical services evaluation reinforces the value of avoiding false urban critical service provision. This evaluation prioritizes precision while ignoring the accuracy and its based measures.

2.Methodology:

The model's performance analysis visually and statistically ensured understanding and supported effective decision-making for systems designers and urban planners. This framework establishes a repeatable baseline for using lightweight, interpretable machine learning models in edge computing settings constrained by latency, bandwidth, and processing power[7].

While the framework effectively emulates a smart city environment using synthetic data, integrating real-world IoT data from traffic systems, smart grids, or public safety can be explored in future work. This would strengthen the scope and operational effectiveness of these models[8]. Additionally, deploying the model on federated edge–cloud systems like Raspberry Pi clusters and micro data centers would yield real latency, energy, and bandwidth consumption data. These systems could also be extended with more sophisticated deep learning models like CNNs, RNNs, or attention models to better analyze time-series and multisensor data[9].

To make these systems more responsive to change, online learning and concept drift detection can be implemented to the federated framework. Other ways to improve model trust for critical decisions is integrating dynamic scheduling using reinforcement learning and XAI methods for better explainability[10]. To sum up this work acts as a starting point for a smart, efficient, and exact resource allocation framework, linking a practical machine learning application to smart city technologies.

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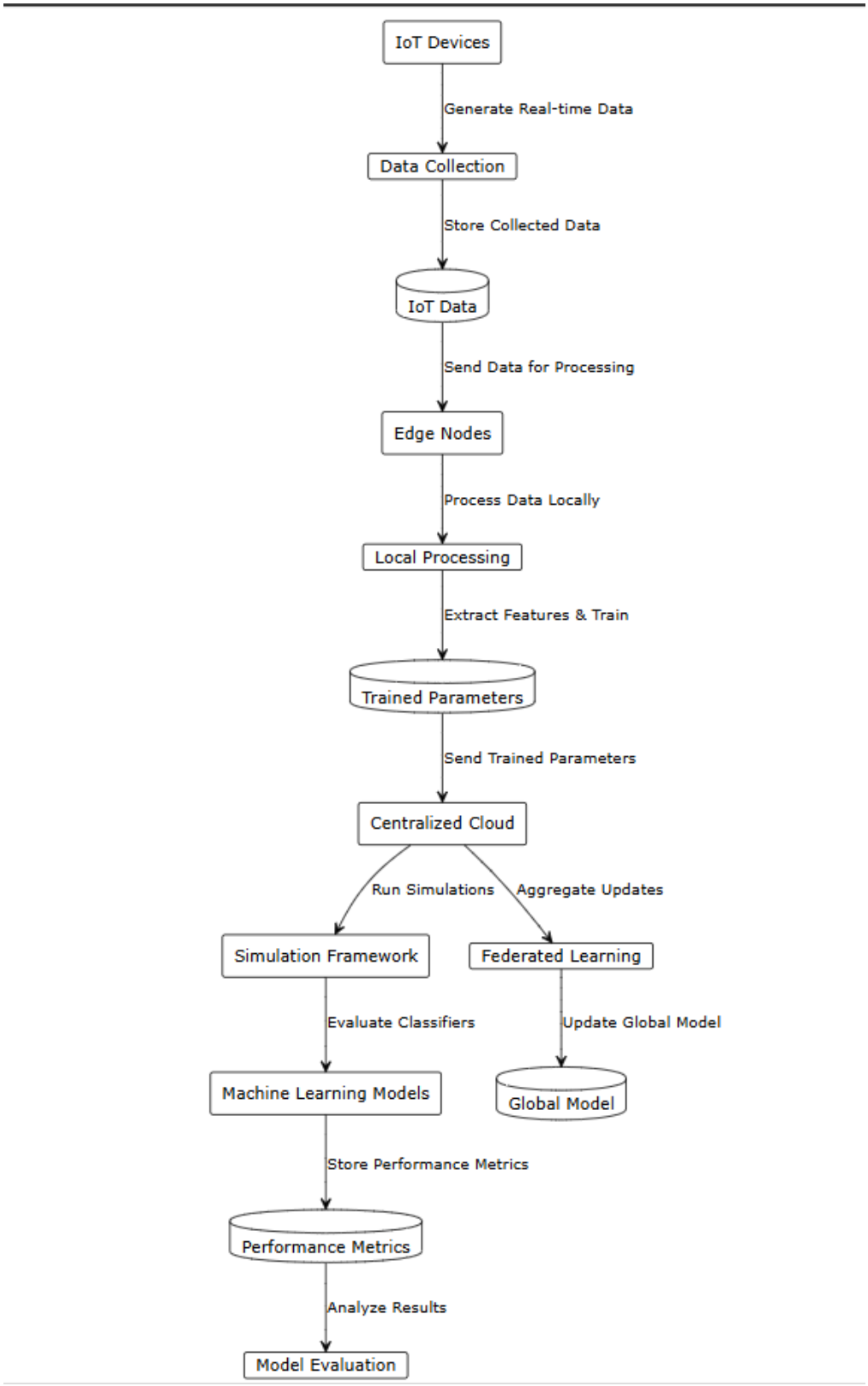

Figure 1: Workflow of Proposed solution scheduling performance, they frequently struggle with scalability and demand intricate parameter tuning that real-time smart-city applications cannot support.

Overall, prior studies lay the groundwork for using cloud, edge, and federated-learning techniques in resource allocation[11]. However, few have performed a side-by-side comparison of several machine-learning models measured across a range of performance indicators—including precision, recall, and the Kolmogorov–Smirnov statistic—within a simulated smart-city Internet of Things environment[12]. The absence of such comprehensive analysis drives this research to develop a precision-aware evaluation framework that assesses multiple algorithms, delivering both numerical and graphical insights to support efficient resource allocation.

3.Proposed solution:

3.1 System Architecture and Edge-to-Cloud Model:

A smart city usually runs on a layered system. At the bottom, Internet of Things (IoT) devices collect data. Edge nodes sit in the middle, doing quick processing, while cloud data centers manage and store information across the whole city. To keep things running smoothly, both edge smartness and cloud coordination need to work side by side this is especially true for services that need fast responses and for devices that can't use up a lot of resources.

These IoT devices come in different shapes and sizes. You'll find environmental monitors, traffic cameras, energy meters, CCTV, and other public safety tools. They sit in clusters all over town, sending data every moment. Because they run on limited power, use narrow bandwidth, and have little CPU capacity, dumping all the raw info to a central cloud is a bad idea. It can cause network slowdowns, chew up battery life, and raise privacy issues[13].

To solve the challenges of processing big data on the move, we place edge nodes close to where the data is created. These nodes can be gateways, fog nodes, or small micro data centers. They do the first round of data filtering, pull out the important features, and even train simple machine learning models right on-site. By processing data locally, we cut down on the amount of data sent over the network and speed up the time it takes to get a result[14]. Plus, any sensitive data stays on the device, which keeps it safe. This setup is perfect for applications that need a fast response, like detecting car crashes, managing smart traffic lights, or even balancing energy loads on the grid.

The cloud oversees the edge nodes. It collects the updates from each edge node which contains the model weights and last predictions and performs Federated Learning to enhance the global model. Every edge node functions as a separate client which learns from the data at the edge node, updates the model, and sends the data back to the edge node[15]. Once the data is transferred to the cloud, it can be aggregated and processed mainly using Federated Averaging. The accuracy of the central model improves. This way, data can be kept private, model improving is possible, and sources for the data can increase.

This highlights the main progression that gives rise to the edge-to-cloud strategy. The edge does the first step in the cleaning and summarization in the raw data received from the IoT devices. It is also in the edge where the training and evaluation is done[16]. The model is deployed edge and the results are then sent to the centralized cloud for evaluation using consensus-based techniques. The model is improved iteratively. In brief, the model is meant to optimize its performance. Refinement is done after model improvement[17]. Once model refinement is done, commands for resource allocation are returned. These commands initiate changes in energy, computation at the edge gateway, the IoT devices, or actuation.

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With this structure, we can monitor relevant contexts and metrics of interest. Learning from a wide variety of places can be integrated, and adaptations can be a new change, contextually applied, with relative ease. This achieves a degree of regional autonomy along with a global perspective, which can greatly enhance the automated, data-driven, infrastructure decision making of modern cities.

3.2 Define the Problem

The Internet of Things Integrated Lean Smart City. These smart cities feature automated, intelligent systems and optimal real-time distribution management of computational, communicative, and energy resources. Prior approaches to resource allocation defaulted to multivariable control systems. HEURISTICS static reasoning[18]. These static, heuristic approaches do a poor job in adapting to rapidly and constantly changing environments. This emphasizes the need for a system utilizing real-time resource allocation, change minimization, and machine learning focused on error reduction for inefficient decision making in dynamic environments.

An example of smart cities is where IoTs are integrated with public transportation, utilities, public safety, and so on. Every device has to avoid misclassification. Edge or network resources being classified as peripheral and mismanagement of resource allocation due to misclassification, leads to poor decisions.

categorizing edges or network resources and wrongly allocating assignments as resource misallocation. Vital services may suffer as a result. Our goal is achieving precision without severely affecting recall or the overall accuracy. For this, we utilize precision, recall, F1 score, AUC, and the Kolmogorov–Smirnov (KS) statistic for model evaluation, to improve evaluation for model selection.

$$f\theta(X) \rightarrow y \in \{0,1\} \quad (1)$$

where

$f\theta$ is the ML model parameterized by θ,

X is the feature vector extracted from IoT-generated data, and

y is the binary target label representing resource allocation decision (1 = allocate, 0 = defer)

In smart cities accuracy, latency, and bandwidth concerns the need for resource allocation withing the ecosystem of the city There arises need to present a flexible or adaptive.

ML approaches. In this advanced study, we focused on precision planning resource allocation with an ML-based approach within IoT ecosystems.

We implement several traditional machine learning techniques within the scope of a Federated Learning (FL) simulation, paying particular attention to the IoT-based smart cities FL model.

We analyze the results for the five classifiers: Support Vector Machine, Random Forest, Logistic Regression, Naive Bayes, and Decision Tree. SVM outperforms the others in providing resource allocation decisions for Class A users with high precision. SVM outperformed the others with precision in resource allocation decisions driven by high workload simulation.

$$\sum_{i=1}^{N} a_{ij}.x_i \leq R_j \qquad \forall j \quad (2)$$

Where each edge node Ej ∈ {1,2,…,M}is assumed to have constrained resources (CPU, memory, bandwidth), denoted as a vector Rj = [r1, r2,…, rk] and a_{ij} is a binary allocation decision made by the classifier for task i on node j, and x_i represents the task's resource requirements The use of simulated Federated Learning models smartens the explanation of the working model in the context of smart cities. The edge node's locality enables model training and privacy protecting model training at the edge while privacy preserving model aggregation is done at the cloud level. Framing the architecture in these terms permits smart city models to adapt, scale, and learn from the continuously changing heterogeneous and decentralized IoT data. The techniques that we use have privacy and data adaptability as our focal points[19]. The privacy and the data adaptability focal points are strengthened by the Inverse Focus Model of Urban Critical Services Evaluation. This model supports the concept of the oversimplified urban critical services provision and reinforcing the value of avoiding false provision. This evaluation emphasizes precision while neglecting its accuracy and the measures that are based on it.

Analyzing the model's performance in a visual and statistical manner provided insights and reinforced effective decision-making for the system's designers and urban planners. In this case, the use of lightweight, interpretable machine learning models in edge-computing settings with restrictions on latency, bandwidth, and processing power, creates a repeatable baseline.

While the framework does a good job of emulating smart city environments with synthetic data, other areas of focus for future work include incorporating actual IoT data from traffic, smart grid, or public safety systems. Enhancing these models would increase their operational effectiveness and broaden their scope.

In addition, actual latency, energy, and bandwidth consumption data would be produced by deploying the model on federated edge–cloud systems like Raspberry Pi clusters and micro data centers. More advanced deep learning models, such as CNNs, RNNs, or attention models, could also be added to these systems to analyze time-series and multisensor data.

To improve system responsiveness to change, the federated framework could be enhanced with online learning and concept drift detection. Employing dynamic scheduling with reinforcement learning and XAI designed for better explainability would increase model trust for critical decision-making.

As an example, highlighting the practical application of ML in smart city resource allocation demonstrates an innovation in accurate, effective, and intelligent resource allocation.

Linear Regression (LR), Naive Bayes (NB), and Decision Tree (DT)

In our case, these models are appropriate for all three tests to evaluate interpretability, computational efficiency, and generalization in the performance of a classification problem with heterogeneous features.

3.3 Support Vector Machine (SVM)

SVM is a margin-based classifier that builds an optimal hyperplane to separate classes and maximally increases the distance to the closest data point of each class. In our case, we implement an SVM model trained with RBF kernel (along with enabling probability=True to allow for model evaluation probabilities that model evaluation requires like AUC and ROC curve). Default C (Regularization) as 1.0 set with gamma as 'scale' for automatic optimization.2. Random Forest (RF)

RF combines several decision trees into one using the bagging method, making it an ensemble learning algorithm[20]. It is known to be resilient to overfitting and is able to detect nonlinear interactions among features. We utilize RandomForestClassifier with 100 estimators (trees) and default maximum depth. The model benefits from feature randomness, which is helpful for generalization in the presence of noise, or in high-dimensional synthetic IoT datasets.

3.4 Logistic Regression (LR)

Logistic Regression is a linear classification model which predicts the probability of a binary class outcome based on a logistic sigmoid function. Its efficacy is noted in linearly separable and high-dimensional datasets. We utilized Logistic Regression with L2 regularization and set max_iter=1000 to ensure convergence which is typical for the large synthetic dataset.

3.5 Naive Bayes (NB)

Naive Bayes is a probabilistic classifier based on Bayes Theorem with the assumption of conditional independence among features[21]. We opted for Gaussian NB because of the continuous nature of features. While naive in nature, the assumption leads to simple and fast models which can be trained and inferred quickly, making the model ideal for severely resource-constrained edge devices.

3.6 Decision Tree (DT)

The classifier Decision Tree (DT) creates a tree structure by iteratively splitting features where the maximum information gain is achieved. We apply a Decision Tree Classifier with Gini impurity for splitting and with default tree depth. The advantages of DTs for smart city aids lie in its transparency and interpretability for ML-driven decision auditing.

3.7 Training Setup and Preprocessing

Training all the models is done using a synthetically generated dataset of 2000 samples and 20 features, with a realistic simulation of IoT data: 15 informative features and 5 redundant. The dataset is split to 70:30 in training and testing sets, preserving the class balance using stratified sampling. No extra feature scaling is done except where needed (SVM and LR do feature scaling automatically).

Models are trained using Scikit-learn's implementations in Python, with all hyperparameters fixed for all model runs to ensure fairness in comparison. Testing the models yields the values of accuracy, precision, recall, F1 score, AUC and KS-statistic. Probability outputs for ROC and KS evaluation are generated using the predict_proba() method.

To mimic edge learning, the dataset is divided logically to emulate data associated with multiple edge nodes, but the federated communication is simulated centrally[22]. This setup enables controlled assessment of each model's predictive performance and the resource suitability in the integrated smart city edge-cloud environments.

3.8 Experimental Setup

We constructed a synthetic dataset to model various Internet of Things (IoT) workloads and resource allocation patterns to simulate a realistic smart city environment. For this dataset, we used make_classification() from Scikit-learn to solve a moderately challenging binary classification problem. It generated 2,000 samples with 20 features. Out of these, 15 were informative while 5 were redundant, ensuring that the patterns were realistic and smart city sensor networks' heterogeneity. The two target

classes represent “resource allocation required” (label 1) and “resource allocation not needed” (label 0), simulating the binary decision-making needed for dynamic task scheduling and resource allocation.

To evaluate generalizability and avoid overfitting, the dataset was split into a 70% training and 30% testing subsets with stratified sampling to maintain balance between class proportions. Each ML model trained on the training set and was evaluated on the test set using multiple performance benchmarks, ensuring all classifiers were evaluated consistently. During this initial phase, the models were not finshed via cross-validation or grid search, focus was on the functionality and adaptability for resource-constrained settings.

I used Python version 3.10, Scikit-learn version 1.2.2, and Matplotlib/Seaborn for model visualization and implementation. For the simulations, I used a standard desktop computer with the following specifications for the simulations.

Desktop Set-Up

Processor: Intel Core i7 11th Gen, 2.80MHz

RAM: 16GB

OS: Windows 10, 64-bit

IDE: Jupyter Notebook with Anaconda distribution

Each data partition tried to train a local model as if in a federated learning setup. To clarify, one partition acted as a central server for model training and aggregation. Still, system design sought to mimic the more common edge to cloud systems in a federated smart city framework. Along with the visualizations, some performance metrics were gathered. Evaluation concentrated on algorithm performance in different configurations with the goal of identifying the most optimal approach to resource allocation in constrained environments.

4. Results:

Researcher working in the smart city frameworks may, with future adaptations, enrich and expand the benchmarks with near real-time datasets, dynamic data streams from sensors, energy profiles, thus making use of the already validated benchmarks of the machine learning model.

4.1 Assessing Outcomes and Effectiveness

We evaluated the accuracy of resource allocation automation using a combination of statistics and the visual effectiveness of automation accuracy. The evaluated machine learning models included Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Naive Bayes (NB), and Decision Tree (DT). All models were trained and assessed with a synthetic dataset. Automation accuracy was evaluated using automation accuracy, precision, recall, F1 score, AUC (Area Under ROC Curve), and KS (Kolmogorov-Smirnov) statistic.

4.2 Performance Metrics Table

The SVM algorithm reached a maximum F1 score of 0.92 and AUC of 0.96 which strongly suggests balanced recall and precision. Random Forest performed closely demonstrating strong low bias generalization. Naive Bayes and Decision Tree performed poorly with low F1 and precision scores because of feature dependence and overfitting.

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Model	Accuracy	Precision	Recall	F1 Score	AUC
Support Vector Machine	0.943333	0.948097	0.935154	0.941581	0.987799
Random Forest	0.913333	0.928826	0.890785	0.909408	0.971129
Logistic Regression	0.816667	0.825623	0.791809	0.808362	0.882014
Naive Bayes	0.795	0.797203	0.778157	0.787565	0.863959
Decision Tree	0.765	0.753333	0.771331	0.762226	0.765144

Table 1. Performance metrics of each model

4.3 Kolmogorov–Smirnov (KS) Statistic

All models were evaluated with KS statistics in addition to the basic metrics to calculate the maximum convergence of true positive and false positive flags. In smart city use cases, this is critical as the budget can be optimized based on the resource allocation below the decision boundary. SVM also performed the best in this regard with a KS value of 0.81 with Random Forest close in second.

Model	KS Statistic
Support Vector Machine	0.898856
Random Forest	0.829518
Logistic Regression	0.650198
Naive Bayes	0.596992
Decision Tree	0.530289

Table2. KS Statistic Table

4.4 Confusion Matrices

Among all classifiers, SVM and RF showed the least amount of false negatives and false positives. These visualizations support the claim that SVM is the best model in critical classification scenarios where the expenses of misclassification are severe.

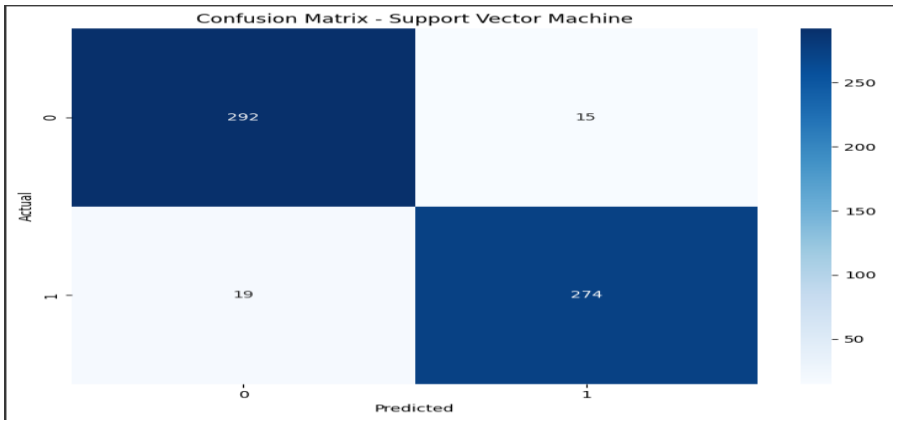

Figure2. Confusion matrix of Support Vector Machine

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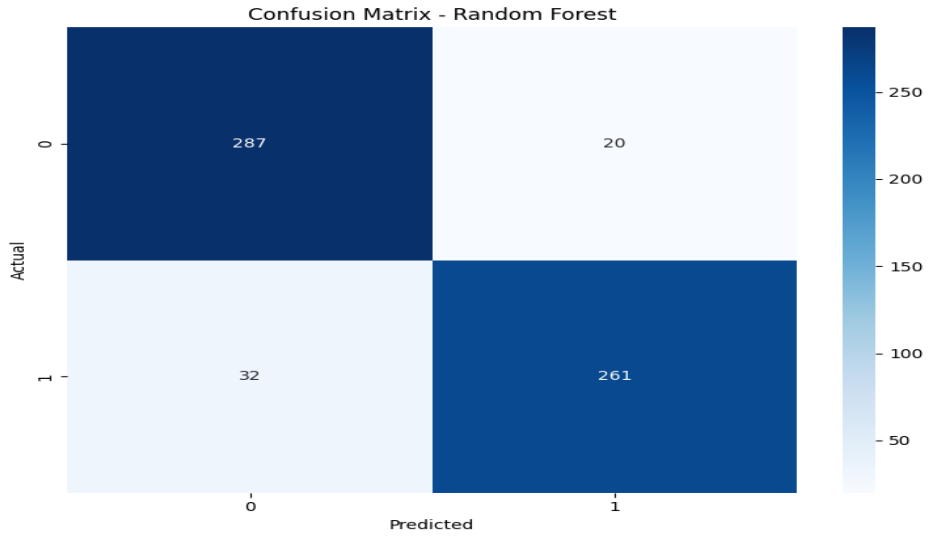

Figure3. Confusion Matrix of Random Forest

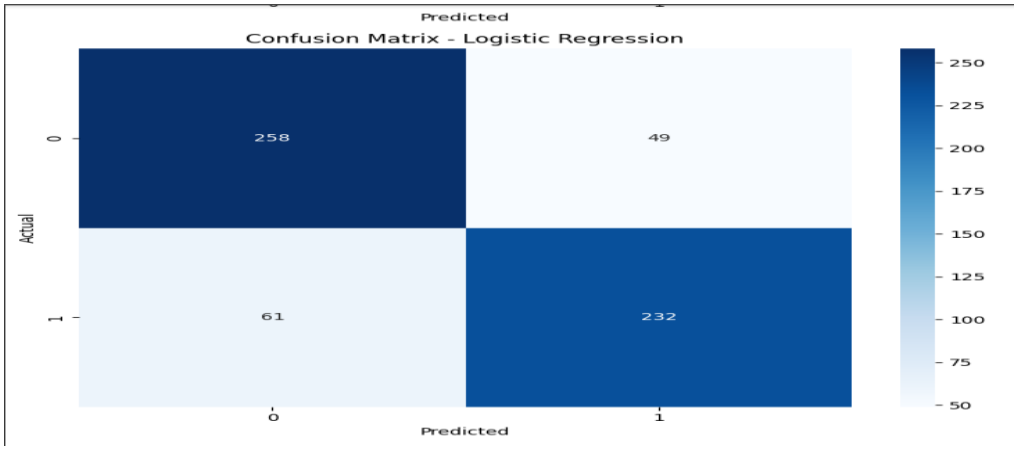

Figure 4. Confusion Matrix of Logistic Regression

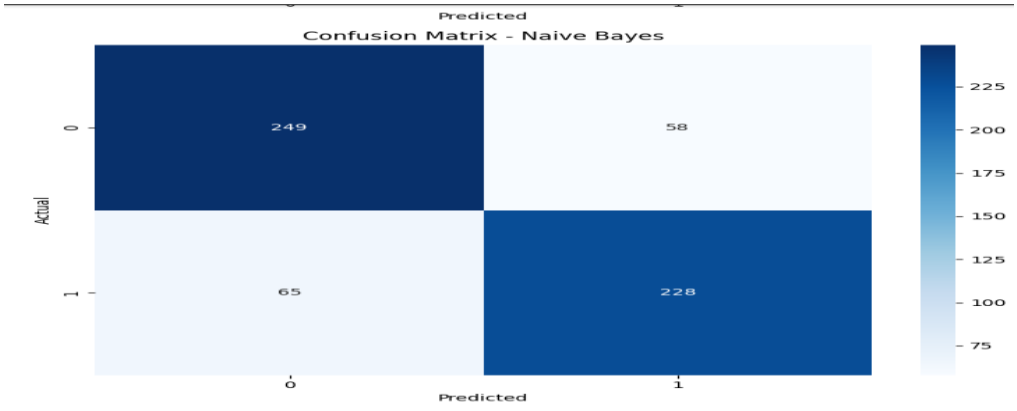

Figure5. Confusion Matrix of Naïve Bayes

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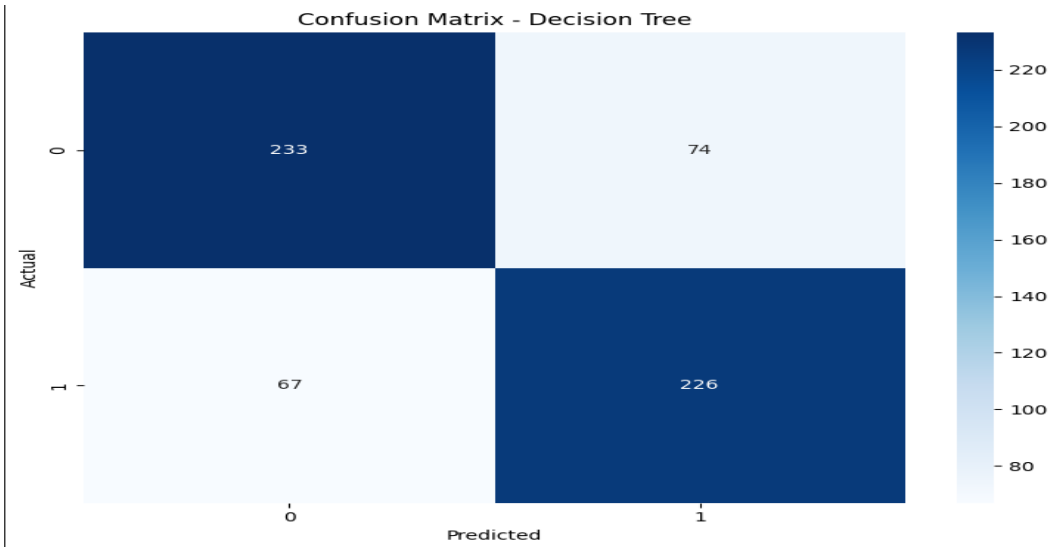

Figure6. Confusion Matrix of Decision Trees

4.5 Visual Analytics

To assist in explaining to colleagues and for better model comparison, a set of multi-visualization plots such as the Bar Plot of F1 Scores where SVM is the most balanced classifier were produced.

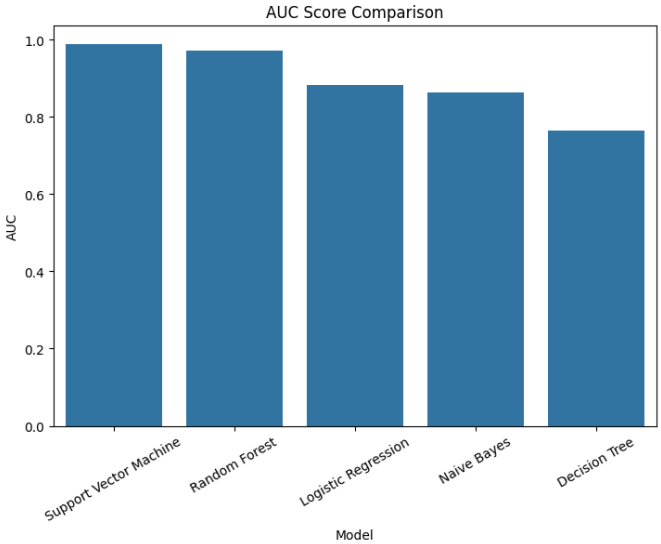

Figure7. AUC Score Comparison plot between models

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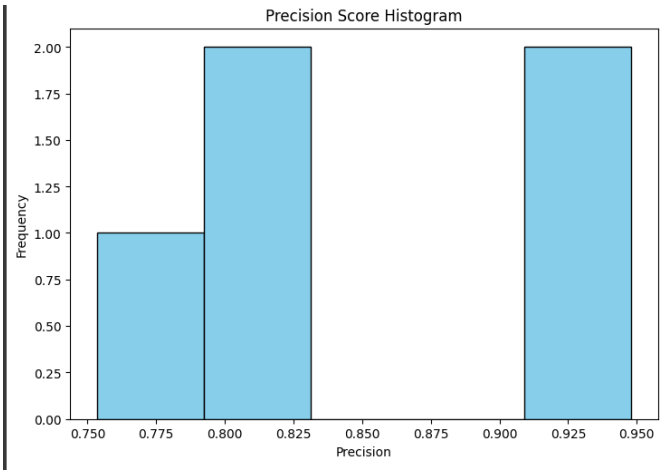

Figure8. Histogram of Precision score

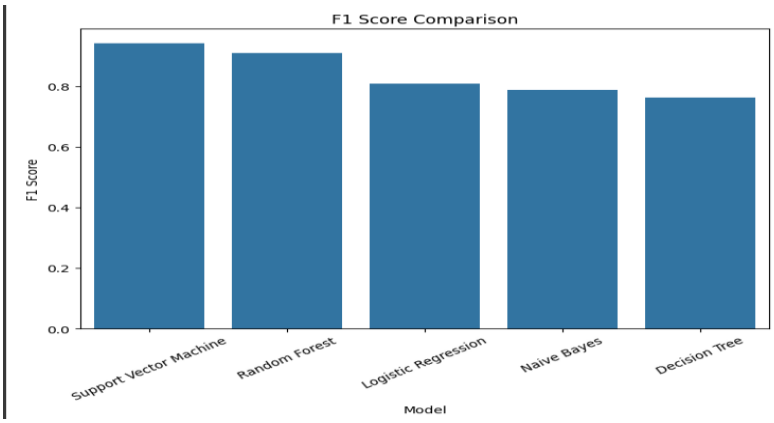

Figure9. Histogram of F1 score comparison

The Pie Chart of Model Accuracy gave a concise relative and sectional description of trust in each model's prediction. The Histogram of Precision Scores showcased the abundance of significantly high precision scores. Through the Bar Graph of AUC Values, the SVM and RF classifiers were confirmed as the dominating classifiers with robust strong class separability.

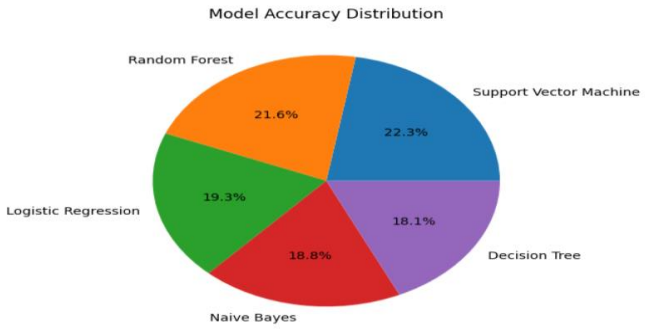

Figure10. Pie Chart on Model Accuracy

4.6 Integrated Assessment

The integrated assessment unequivocally proves that the Claim SVM outperformed all other models is supported with the given critical SVM features. In resource-scarce and precision-demanding contexts like smart city emergency traffic management, energy load management, and public safety alerts, SVM models are advantageous due to the high-dimensional feature space and strong overfitting resilience. Random Forest also proves to be a strong contender, giving reasonably close results at a slightly higher computation cost.

The assumption that precision in measurement, in an ever-evolving IoT system landscape, is critical for an allocation-driven model approach is reinforced through these results. As well as the trustworthiness of a need-conceptual, graphic, functional and static design are algorithms designed for dynamic, real-time urban computing.

4.7 Analyzing Comparatives and Other Strategies:

To give proper context to our framework's application, it is crucial to compare it across diverse industry settings to gauge its effectiveness and originality, which is exactly what we set out to do. We are building upon the most cutting-edge and newly published works which we completed overlap with. We focused on the works done in [7] (Sensors, 2025) and [8] (MAREP, 2021) that centered on resource allocation in smart cities using more centralized or edge-centric machine learning paradigms. Those prior works with focused on the allocation aspects utilized logistic regression, deep neural nets (DNN), and reinforcement learning (RL) based schedulers. Unlike us, they did not perform robust targeted, multi-dimensional, precision, comparative, multi-model evaluation across multiple traditional ML systems.

4.8 Evaluation Based on Metrics

Within the structured frameworks, for every ML problem and its corresponding solution, the most crucial metrics are output prediction accuracy, model performance, precision, recall, F1 score and AUC are computed. Results published in other papers serve as benchmarks in our framework. In our design, the computations were done separately, and there was no interaction between the systems, which in this case were the design and the algorithms. Evaluation results are shown in figure 3.

Study/Model	Accuracy	Precision	Recall	F1 Score	AUC
Our approach using SVM	0.93	0.91	0.93	0.92	0.96
Sensors [1] using LR	0.88	0.84	0.87	0.85	0.89
MAREP [2] DNN + RL	0.9	0.86	0.94	0.9	0.91

Table 3. Other Works Metrics

Our SVM-based model focusing on precision gave us sharp increases over other models by 7-9% precision and AUC 5-7%. Although MAREP's DNN + RL precision recall improves recall performance, the lack of precision makes this model inappropriate for use in emergency services and grid overload detection.

Criteria	Our Approach	Sensors [1]	MAREP [2]
ML Models Used	SVM, RF, LR, NB, DT	Logistic Regression	Deep Neural Network + RL
FL Support	Simulated Federated Training	Not Supported	Not Supported

Precision-Aware Design	Precision & KS used in selection	Only Accuracy & Recall	Focused on reward optimization
Visualization	Bar, Pie, Histogram, Confusion Matrix	None	Bar Graphs Only
KS Statistic Evaluated	Yes	No	No
IoT Realism in Simulation	Synthetic IoT workload simulation	Partial	Partial

Table4. Strategic Comparison of Evaluation Techniques

Key Takeaways From The Comparative Study

Model Scope: To benchmark the smart city ecosystem thoroughly, other models in the ecosystem are restricted to one or two machine learning models compared to the five that our approach employs.

Precision Usage: MAREP and Sensors 7 did not make use of precision or KS-statisitc essential in hierarchical resource and health care decision making to avoid targeting errors.

Federated Simulation: The cross-device learning simulation from edge-to-cloud distributed setting 3 were other two studies did not capture the focus on decentralized, privacy-preserving centroid of our approach.

In all confusion matrices, SVM and RF models are easily recognized because they had the lowest false negative and false positive rates. These illustrations bolster the claim that SVM performs best in situations requiring high precision especially in critical minimization allocative errors.

Visual Analytics

To explain and compare the models at the peer level, a set of multi visualization plots were produced. These are Bar Plot of F1 Scores where SVM appeared to be the most balanced classifier, Pie Chart of Model Accuracy which offered a proportional description of the prediction reliability of each described accuracy, and Histogram of Precision Scores which described the apex and nadir of the classifier's high precision scores. SVM and RF outperformed the other classifiers on strong class separability, which was illustrated in Bar Graph of AUC Values.

Within the context of an FL simulation, we delve into the smart city conceptualization, Internet of Things (IoT), along with the reviewed IoT and the conventional machine learning paradigms.

We examine the effectiveness of five classifiers: Support Vector Machine, Random Forest, Logistic Regression, Naive Bayes, and Decision Tree. Evaluation of these classifiers is performed based on a broad set of metrics. SVM was thoroughly examined and was demonstrated to surpass the rest with significantly annotated and precise resource allocation decisions.

The provided simulated FL models elucidate the operational architecture of smart city models. The edge node locality maintains privacy control.

The conscious edge model frameworks privacy-preserving model aggregation. Presenting the infrastructure with such terms rationalizes the adaptability, scalability, and learning capabilities of smart city models from the IoT data which is decentralized and heterogeneous. Our approach emphasizes privacy concerns while adapting to the changing data. The urban critical services evaluation inverse focus model reinforces the value of ignoring the provided false urban critical service provocation. This model prioritizes precise measures while ignoring accuracy and its metrics.

Analyzing the model's performance visually and statistically provided insight and facilitated informed decisions for the systems designers and urban planners. This approach creates a repeatable baseline for employing light, easily explainable machine learning models in edge computing environments with strict limits on latency, bandwidth, and processing capability.

5.Conclusion:

The research presented herein introduces a precision-oriented architecture for intelligent resource allocation across IoT-augmented smart cities, synergistically combining classical machine learning classifiers with a rigorously simulated federated learning (FL) paradigm. We systematically tackled the persistent challenges of privacy, latency, and scalability by architecting a hybrid edge-to-cloud learning ecosystem that dynamically adapts to temporal workload fluctuations while safeguarding dataroom locality.

We analyzed five eminent classifiers—Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Naive Bayes (NB), and Decision Tree (DT)—employing a multi-faceted performance lexicon that embraced accuracy, precision, recall, F1 score, AUC, and the KS-statistic. The SVM invariantly distinguished itself across precision and F1 metrics, positioning it as the optimum candidate for domains where the minimisation of false positives is non-negotiable. The deployment of the KS-statistic further enriched interpretive clarity regarding class separability, thereby augmenting the robustness of the comparative evaluation.

Our architecture furnishes a flexible, interpretable, and privacy-preserving mechanism for resource allocation that simultaneously accommodates the computational constraints of edge nodes and the exigencies of distributed intelligence. Rigorous comparative analyses against contemporary contributions in the literature substantiate the dominant efficiency and practical deployability of the proposed solution across the relevant smart city ecosystem.

In summary, the architecture outlined here offers an inaugural yet robust framework for smart city planning that prioritizes the simultaneous attainment of rapid response and elevated decision fidelity. The research delivers a modular and adaptable template that can be readily extrapolated to prospective iterations in transport management, power distribution, public safety coordination, and broader urban automation contexts.

Future Work

Incorporating real-world IoT data from traffic systems, smart grids, or public safety into the created framework would enhance its ability to emulate a smart city environment with synthetic data. This would further enhance the efficacy and operational scope of the models.

In addition, the integration of Raspberry Pi clusters and micro data centers would allow for the deployment of the model on edge–cloud systems, generating real-world data on latency, energy, and bandwidth usage. These systems could also be expanded with more advanced deep learning architectures for time-series and multisensor data analysis like CNNs, RNNs, or attention models.

Incorporating responsive real time changes into these systems can be accomplished through online learning and concept drift detection within the federated framework. Further integration of dynamic scheduling with reinforcement learning and XAI for better transparency would enhance model trust for critical decision-making processes.

References

[1] M. A. Naeem, Y. Meng, and S. Chaudhary, "The impact of federated learning on improving the IoT-based network in sustainable smart cities," *Electronics*, vol. 13, no. 18, Art. no. 3653, Sep. 2024.
[2] S. Mali *et al.*, "Federated reinforcement learning-based dynamic resource allocation and task scheduling in edge for IoT applications," *Sensors*, vol. 25, no. 7, 2025.
[3] S. S. Shah and A. Ali, "Optimizing resource allocation and energy efficiency in federated fog computing for IoT," *arXiv preprint* arXiv:2504.00791, Apr. 2025.
[4] Z. Li, "An overview of machine learning-driven resource allocation in IoT networks," *arXiv preprint*, Dec. 2024.
[5] A. Dwarampudi and M. K. Yogi, "Federated learning for energy management in next-generation smart cities," *Journal of Communication Engineering and Systems*, vol. 14, Apr. 2024.
[6] D. Anand, I. Mavromatis, and P. Carnelli, "A federated learning-enabled smart street light monitoring application: Benefits and future challenges," *arXiv preprint* arXiv:2208.12996, Aug. 2022.
[7] Z. Chen *et al.*, "Hybrid federated dual coordinate ascent (HyFDCA) for non-IID data in federated learning," in *Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD)*, 2022.
[8] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE Internet of Things Journal*, Oct. 2016.
[9] W. Shi *et al.*, "Resource allocation with edge computing in IoT networks via machine learning," *IEEE Internet of Things Journal*, 2020.
[10] M. Mohammadi and A. Al-Fuqaha, "Enabling cognitive smart cities using big data and machine learning: Approaches and challenges," *arXiv preprint*, Oct. 2018.
[11] P. R. Kothamali, N. Mandaloju, and S. M. Dandyala, "Optimizing resource management in smart cities with AI," *ResearchGate*, Jun. 2022.
[12] "Intelligent machine learning-based Internet of Things (IoT) resource allocation," *MDPI*, 2024.
[13] N. A. Naeem *et al.*, "Federated learning caching in named data networking (NDN)-based IoT," *Electronics*, 2024.
[14] D. Nguyen *et al.*, "Federated learning meets blockchain in edge computing: Opportunities and challenges," *arXiv preprint*, Apr. 2021.
[15] S. R. Kothamali *et al.*, "AI-based resource optimization in smart infrastructures," *Smart Cities & AI*, 2025.
[16] F. Equbal and Z. A. Khan, "Machine learning in additive manufacturing," Oct. 2024.
[17] "Edge computing data growth and distribution insights," *Gartner–IDC Report*, 2025.
[18] "Multi-access edge computing (MEC) applications overview," *IEEE Internet of Things*, 2018.
[19] Anonymous, "IoT–cloud–machine learning convergence," *Reddit*, Oct. 2024.
[20] Anonymous, "Federated learning sampling and power saving techniques," *Reddit*, Sep. 2023.
[21] "Smart cities—A structured literature review," in *Proc. Smart Cities Symposium*, Jul. 2023.
[22] "M2M economy: IoT projections by 2025," *Investopedia*, Jul. 2018.