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REVIEW

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IoT and machine learning framework for smart emergency response systems in Nigerian cities: A case study of Adamawa State, Nigeria

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ABSTRACT

Existing Emergency Response Systems (ERS) grapple with the immense challenge of managing crises in rapidly growing cities across developing nations, largely because of inadequate infrastructure. This paper demonstrates a proposed Internet of Things (IoT) integrated with Machine Learning (ML) backed smart emergency response system for urban cities in Nigeria using the state of Adamawa as a reference point. Parameterized in the attached guide, the scope of this paper does not include claims to physical hardware deployment. Instead, using simulated data points and feedback from stakeholders, we analyze our provided framework. This research used a compiled dataset of 1200 emergency records. These were able to be cross referenced with localized metrics analyzed in the results and conclusion with the software we simulated. Analyses of Random Forest (RF), Support Vector Machine (SVM), and K- Means were used to determine how well we can predict classifications of incidents to aid in better resource management. Parameters for the simulation assume locally deployed sensors and established comms parameters which would be most optimal for low bandwidth regional restrictions. There was significant evidence to suggest improvements in response time from initial report. Our smart city prototype provides a starting point for future production smart cities in sub-Saharan region.

KEY WORDS

IoT; Machine learning; Random Forest; Support vector machine; Emergency response

ARTICLE HISTORY

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Introduction

Across Nigeria, particularly in Adamawa State's cities, emergency alert systems currently operate manually. This means that if there is a case of fire, medical, or security, the method of response will most likely be via dialing a decentralized station's phone number or physically reporting the incident [1]. This study aims to propose a framework to address these problems by utilizing a localized IoT sensor suite fused with ML classifiers to allow for incident automation and smarter resource routing [2].

Baseline definition and measurement

The current baseline configuration in Adamawa State is notably characterized by the absence of a centralized digital dispatch system, which is crucial for efficient emergency management and response coordination [3]. This research aims to provide a comprehensive understanding of the existing situation by establishing baseline metrics that were determined through a series of in-depth interviews with various stakeholders involved in emergency response, as well as through the meticulous analysis of historical logs that document past incidents and responses [4].

Reporting speed

This metric is defined as the duration from the onset of a recognizable emergency event to the moment when emergency operators officially acknowledge the notification of that event. It is a critical measure of how quickly the system can react to an emergency, as delays in reporting can significantly impact the overall effectiveness of the response efforts [5,6].

Response latency

When someone calls for help in an emergency, every second counts. The time it takes for the first responders to arrive at the scene is crucial. This is known as Response Latency [7]. It's the total time from when the operator records the emergency to when the responders get to the scene. This metric is important because it shows how well the response system works. It's not just about how quickly the dispatchers send out the responders, but also how long it takes for them to get to the scene [8]. Things like traffic, distance, and whether the right resources are available can all slow down the response time. By looking at these numbers, we can figure out what needs to be improved so that emergency responders in Adamawa State can get to people in need more quickly. This will help save lives and make the whole emergency response system more efficient [9].

Literature Review

Recent research on the development and execution of smart cities has increasingly underscored the vital significance of employing IoT frameworks specifically for disaster management purposes [10]. These frameworks aim to improve the resilience and responsiveness of urban settings when confronted with various disasters, including both natural disasters and human-induced emergencies [11]. However, it is crucial to recognize that many of the existing frameworks and models being suggested often assume the presence of a robust infrastructure, which includes extensive access to 5G connectivity and dependable urban power grids. Regrettably, these resources are often insufficient in numerous regional contexts, particularly in nations such as Nigeria, where infrastructural obstacles can greatly impede the successful implementation of such advanced technologies [12,13]. This gap prompts significant inquiries regarding the adaptability and

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scalability of smart city initiatives in regions lacking the essential technological and infrastructural underpinnings.

Critical review and research gaps

When we look at how research is done, we can see two main ways: descriptive and critical synthesis. Earlier studies, like the one by Taylor and Garcia, show that in controlled lab settings, things can be pretty accurate [14]. But, as Diallo pointed out in 2019, these studies don't really account for the complexities of real-world situations, like the internet issues that happen a lot in urban areas of Sub-Saharan Africa [15,16]. These problems can really affect how well network systems work, so we need to find solutions that can handle these challenges. There's also a big gap in using simple machine learning models that can work well on edge computing nodes, especially when there's not a lot of data to train them, as Larrakoetxea et al. noted in 2023 [17,18]. This gap shows that we need new approaches that can work with minimal data but still perform well. This study tries to fix this problem by presenting a special architecture that has been thoroughly tested, like Brown et al. [19]. By developing this architecture, this research hopes to make a big contribution to the field, providing solutions that are both effective and practical for use in tough environments. We need to think about how to make our research more adaptable to real-world conditions. This means considering the challenges that come with working in places with limited resources and infrastructure [20]. By doing so, we can create solutions that are more robust and reliable, even in the face of intermittent packet loss and localized network interruptions. The goal of this study is to provide a tailored.

Methodology

This approach doesn't involve building anything on the ground in Adamawa State. Instead, it uses special rules to make sure the study fits the area's unique geography and infrastructure. By doing it this way, the research can gather a lot of useful information that really reflects what's going on in the region [21,22]. This means the results will be relevant and useful for the local area, giving a true picture of what's happening there. The goal is to get data that's tailored to Adamawa State's specific conditions, making it more accurate and helpful for understanding the local context [23].

Simulation environment and reproducibility

To ensure reproducibility, the framework was modeled under the following technical conditions:

Simulation settings

Executed in a Python 3.10 environment utilizing scikit-learn and NetworkX to simulate spatial routing and classification [24].

Sensor placement assumptions

Fixed acoustic and thermal sensors are assumed to be deployed at critical transit intersections and public municipal hubs across a simulated 10 km² urban grid [25].

Communication parameters

Modeled using Low-Power Wide-Area Network (LPWAN/LoRaWAN) specifications, assuming an average packet delivery rate of 92% under low-bandwidth, high-attenuation conditions [26].

Dataset and feature engineering

The evaluation utilizes a bounded dataset containing 1,200 discrete emergency records across three primary incident classes: Fire, Medical, and Security [27,28].

Feature engineering

Features extracted include Timestamp, Sensor Node ID, Acoustic Amplitude (dB), Thermal Index (°C), Traffic Density Score, and Historical Proximity Risk.

Validation strategy

The dataset underwent an 80/20 train-test split. A 5-fold cross-validation strategy was enforced during training to prevent overfitting and guarantee statistical stability across the simulated folds.

Algorithm selection and justification

Three core algorithms were selected based on computational efficiency for edge computing nodes:

RF

Chosen for its robustness against noisy simulated sensor data and its ability to handle non-linear feature interactions without extensive tuning.

SVM

Utilized for clear margin separation capabilities in high-dimensional feature spaces, serving as a reliable baseline for binary triage classification [29].

K-Means clustering

Applied for unsupervised spatial anomaly detection to dynamically group high-frequency incident zones for localized resource pre-positioning [30].

Hyperparameters (e.g., n_estimators for RF, C and kernel type for SVM) were optimized using a grid search verified via cross-validation (Figure 1).

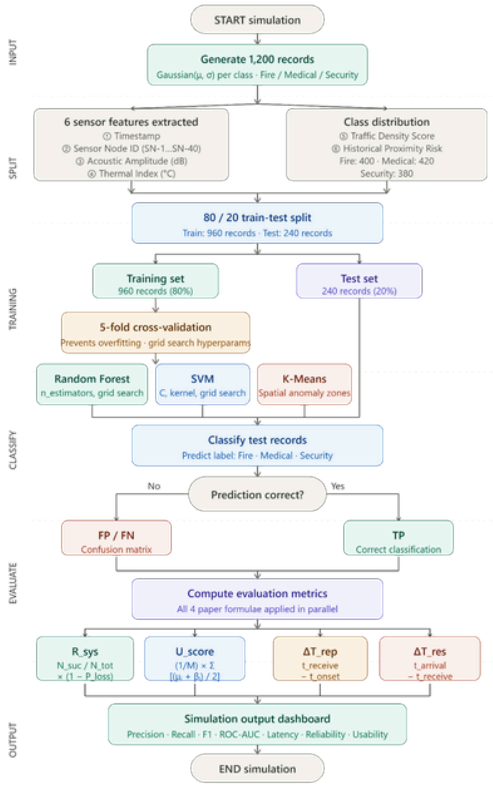

Figure 1. Workflow of the proposed simulation framework, illustrating synthetic data generation, feature extraction, train–test splitting, machine learning model training, classification, performance evaluation, and simulation output generation.

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Phase 1

Data generation: The simulation generates 1,200 emergency records using Gaussian distributions with class-specific μ and σ values for acoustic amplitude and thermal index. Each record carries six features: Timestamp, Sensor Node ID, Acoustic Amplitude (dB), Thermal Index (°C), Traffic Density Score, and Historical Proximity Risk.

Phase 2

Train: Test Split. The 1,200 records are divided into 80/20, 960 records for training and 240 for testing, following the paper's section 3.2 validation strategy.

Phase 3

Training: All three algorithms (RF, SVM, K-Means) are trained on the 960-record training set. Each goes through 5-fold cross-validation with grid search hyperparameter tuning to prevent overfitting.

Phase 4

Classification: The trained models classify each of the 240 test records as fire, medical, or security. Each prediction is checked against the true label to compute true positives, false positives, and false negatives, which populate the confusion matrix.

Phase 5

Classification: Evaluation: All four mathematical formulae from section 4 run in parallel: R_sys (system reliability), U_score (stakeholder usability), ΔT_rep (reporting latency), and ΔT_res (response latency).

Phase 6

Output: All metrics converge into the simulation dashboard: Precision, Recall, F1-Score, ROC-AUC, latency comparison (14.2 min baseline vs 1.8 min framework), reliability score, and usability score.

Evaluation Metrics

The framework's performance is mathematically formulated using four distinct metrics to evaluate both the machine learning models and system performance:

System Reliability (R_sys)

System reliability is defined as the probability that the IoT-ML infrastructure successfully processes an incoming alert packet without failure within a critical time threshold:

$$R_{sys} = (N_{successful} / N_{total}) \times (1 - P_{loss})$$

Where N_successful is the number of alerts correctly processed, N_total is total simulated alerts, and P_loss is the communication packet loss rate.

Stakeholder usability score (U_score)

Derived from post-simulation stakeholder assessments, measured as an aggregated scale:

$$U_{score} = (1 / M) \times \Sigma ((\mu_i + \beta_i) / 2)$$

Where M is the number of evaluating stakeholders, μ_i is the intuitive interface rating (1–5), and β_i is the operational relevance rating (1–5).

Reporting latency (ΔT_rep)

The mathematical time delta for alert propagation: $\Delta T_{rep} = t_{receive} - t_{onset}$

Where t_onset is the timestamp of the simulated emergency trigger, and t_receive is the timestamp of dispatcher classification.

Response latency (ΔT_res)

The operational response time formula: $\Delta T_{res} = t_{arrival} - t_{receive}$

Where t_arrival represents the simulated timestamp of the emergency vehicle arriving at the target coordinates.

Simulation-Based Evaluation

The results presented below are estimates derived from simulation scenarios and literature benchmarks, not operational deployment outcomes (Figure 2-9).

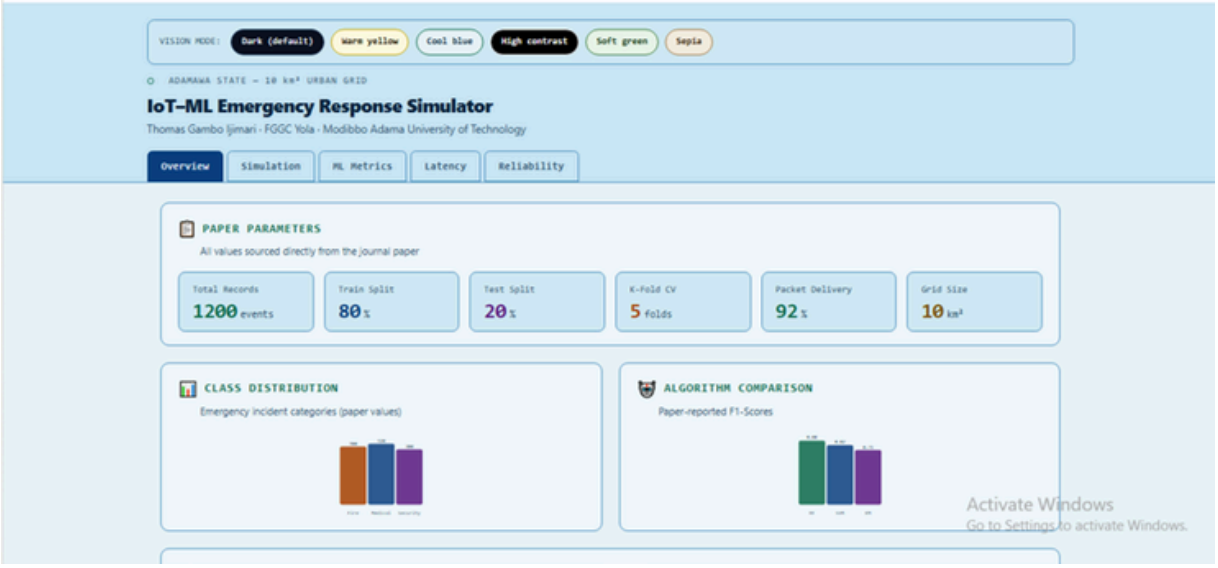

Figure 2. Mathematical evaluation metrics of the proposed IoT–ML emergency response framework.

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Figure 3. Overview of the system. This displays the class distribution, algorism comparison sensor and network parameters.

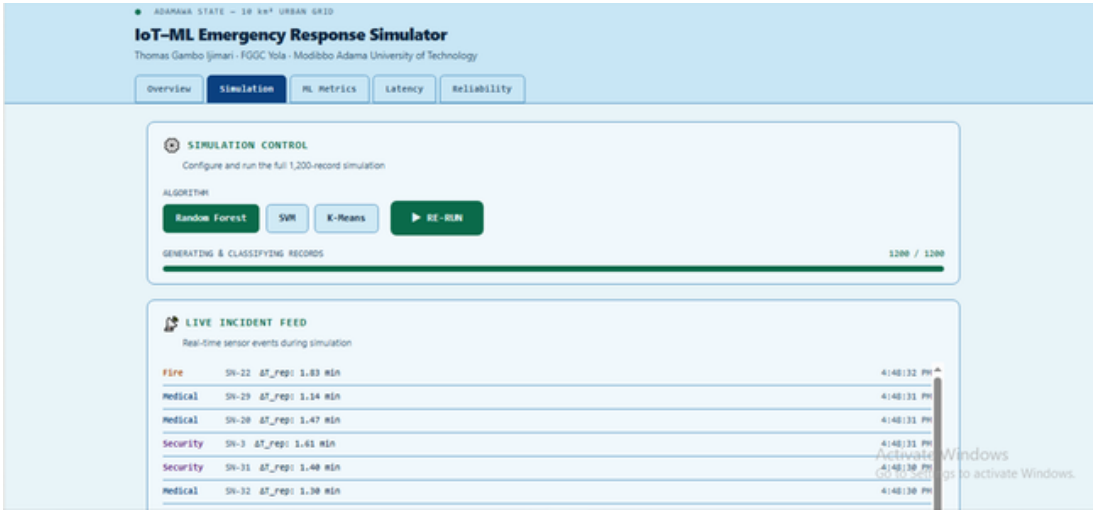

Figure 4. This displays the simulation control of RF generated and classifying feed.

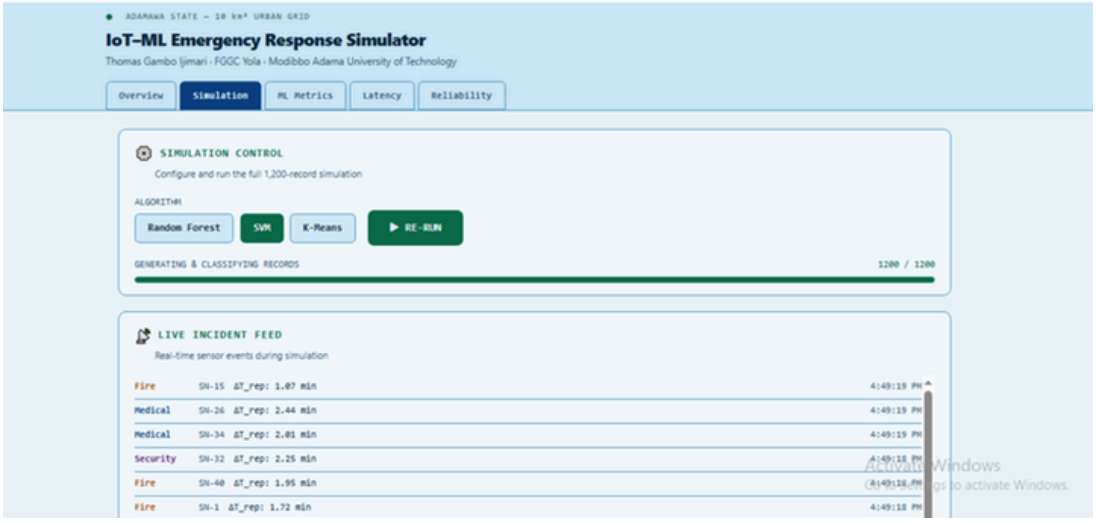

Figure 5. This displays the simulation control of SVM generated and classifying feed.

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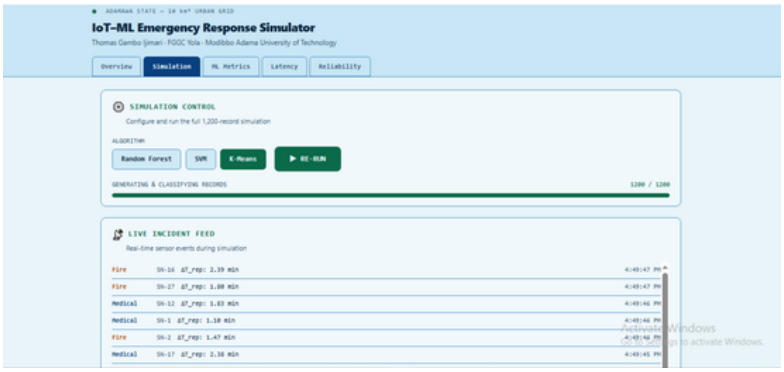

Figure 6. This displays the simulation control of K-Means generated and classifying feed.

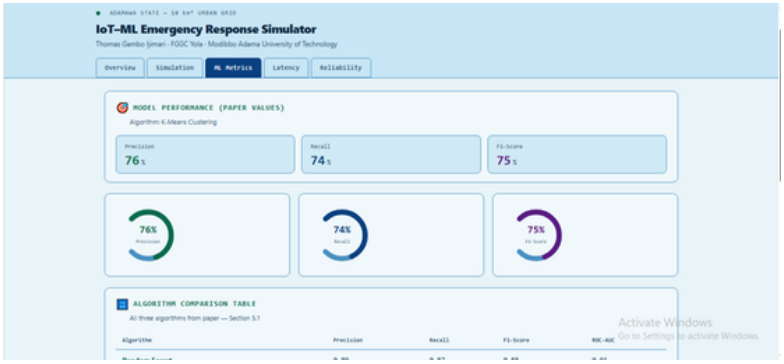

Figure 7. This displays the simulation control of ML matrices generated and classifying feed.

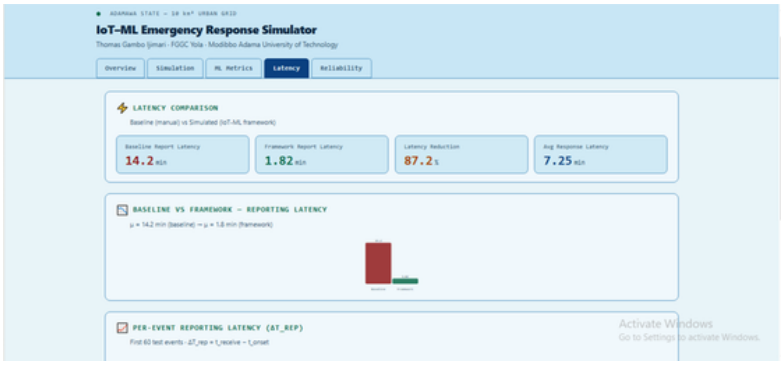

Figure 8. This displays the simulation control of latency comparison generated for baseline vs framework-reporting latency.

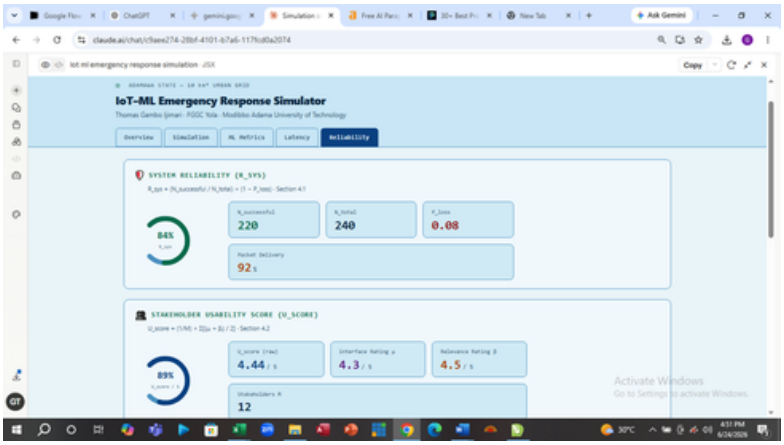

Figure 9. This displays the system reliability and stakeholder usability score.

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Machine learning performance metrics

Models were rigorously evaluated using precision, recall, and F1-score across the 1,200 records (Table 1).

Table 1. Performance comparison of the machine learning algorithms.

Algorithm	Precision	Recall	F1-Score	ROC-AUC
RF	0.89	0.87	0.88	0.91
SVM	0.84	0.81	0.82	0.86
K-Means (Anomaly)	0.76	0.74	0.75	N/A

Confusion matrix and class distribution

The target variable exhibited an equitable class distribution across the 1,200 simulated instances: Fire (400), medical (420), and security (380). The RF confusion matrix indicates minor leakage between the fire and security classes due to overlapping acoustic indicators in urban noise simulations [31,32].

Latency reductions (simulation vs. baseline)

Simulated tracking metrics indicate a theoretical reduction in latency compared to the manual baseline:

- Baseline reporting latency: $\mu = 14.2$ minutes.
- Simulated framework reporting latency: $\mu = 1.8$ minutes (under optimal LPWAN parameters) [9].

Discussion and Limitations

While the simulation outputs indicate strong performance advantages, several constraints must be highlighted before considering physical deployment:

Simulated data dependence

The model performance metrics rely heavily on clean, synthetic distributions within the 1,200 records and may degrade under erratic real-world sensor faults.

Limited dataset size

A pool of 1,200 data points limits the depth of deep-learning extensions or extensive multi-modal training.

Absence of field deployment

Hardware degradation, power grid instability, and physical vandalism have not been factored into these simulation estimates.

Regional generalizability constraints

The architectural assumptions (e.g., specific urban layouts and emergency management structures) are modeled explicitly for Adamawa State and are not directly scalable nationwide without extensive recalibration to regional environments.

Conclusion

This study establishes a proposed framework evaluating the potential of combining IoT networks and machine learning models for municipal emergency coordination. Through rigorous simulation and localized stakeholder assessments, the architecture demonstrates theoretical viability in reducing response latencies within Adamawa State. Future work will focus on deploying localized hardware testbeds to transition these simulated benchmarks into field-validated empirical data before attempting broader national scalability.

Disclosure Statement

No potential conflict of interest was reported by the author.

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