

Article

Machine Learning for CIoT Network Selection in AMI Networks

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Abstract

The evolution of Advanced Metering Infrastructure (AMI) requires reliable, energy-efficient, and scalable communication technologies for connecting large numbers of smart meters and gateways with utility backend systems. Among 3GPP Cellular Internet of Things (CIoT) technologies, Narrowband IoT (NB-IoT) and LTE-M are promising candidates due to their extended coverage, low cost, and power efficiency. However, selecting between them remains challenging because performance depends on deployment environments, spatial distribution, and radio signal conditions. This study addresses the CIoT network selection problem in AMI networks by applying machine learning to predict the appropriate communication technology from smart meter location and Reference Signal Received Power (RSRP). Three supervised learning algorithms, namely Decision Tree, Support Vector Machine, and XGBoost, were evaluated using field measurement datasets from two AMI deployment areas. A spatial holdout strategy was applied to assess performance in unseen geographical regions. Decision Tree achieved the best performance in Area 1, with an accuracy of 0.7143 and an F1-score of 0.6154. In Area 2, XGBoost achieved the highest performance, with an accuracy of 0.9732 and an F1-score of 0.9388. The results demonstrate the feasibility of ML-based CIoT selection under spatially heterogeneous and imbalanced deployment conditions.

Keywords: advanced metering infrastructure (AMI); cellular internet of things (CIoT); NB-IoT; LTE-M; machine learning; technology selection; smart grid communications; reference signal received power (RSRP); spatial analysis

1. Introduction

The digital transformation of electrical utilities through smart grid technologies has made Advanced Metering Infrastructure (AMI) a fundamental component of modern energy management, as illustrated in Figure 1 (graphical illustration generated with the assistance of ChatGPT-5.5). AMI enables bidirectional communication between utility providers and end users, supporting applications such as remote meter reading, outage detection, dynamic pricing, and demand response. As utilities deploy large-scale smart meter networks across urban and rural environments, maintaining reliable, energy-efficient, and context-aware communication becomes a critical challenge for ensuring system scalability and operational responsiveness [1–3].

To address these requirements, Low Power Wide Area Network technologies standardized by the 3GPP, including Narrowband IoT (NB-IoT) [4–6] and LTE-M [7–10], have been widely adopted in AMI deployments. These technologies extend the capabilities of LTE networks to support the massive Machine-Type Communications (mMTC) use case,



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focusing on low data rates, long battery life, and extended coverage. However, they present distinct performance profiles: NB-IoT operates on a narrowband (180 kHz), providing superior coverage and energy efficiency but with higher latency and lower throughput. It is suitable for delay-tolerant, static applications such as periodic meter readings [11,12]. LTE-M, on the other hand, supports features like mobility, voice over LTE (VoLTE), and lower latency, making it ideal for time-critical or interactive applications such as real-time load control or firmware updates [13–16].

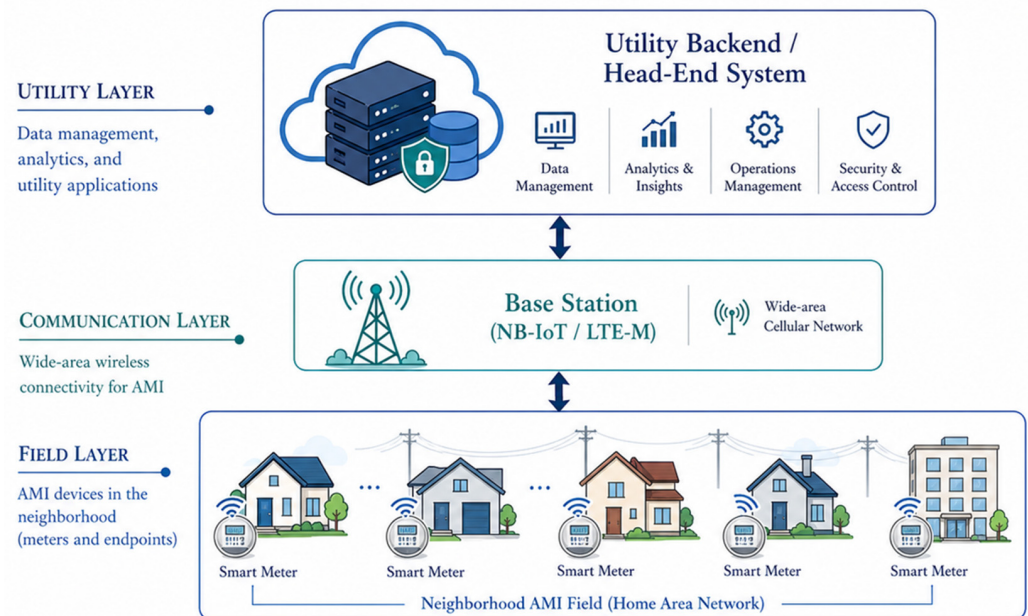


Figure 1. CIoT-based AMI Communication Architecture.

Despite these advantages, the static configuration of communication technologies is often inefficient in practical deployments. Radio conditions vary significantly across locations due to environmental factors, network load, and interference. Signal quality may degrade considerably at the cell edge, leading to communication failures or suboptimal performance when an inappropriate technology is selected. Fixed radio access technology (RAT) selection strategies may result in reduced reliability, increased energy consumption, and violations of quality of service (QoS) requirements, particularly in heterogeneous environments [17]. Conventional CIoT technology selection methods typically rely on threshold-based decision rules derived from signal quality indicators, such as Reference Signal Received Power (RSRP) or Signal-to-Noise Ratio (SNR). Although these approaches are simple and computationally efficient, they may fail to capture the nonlinear and spatially dependent relationships between radio conditions and communication performance. Consequently, such methods may lead to suboptimal decisions in real-world deployments. In contrast to our previous adaptive CIoT selection work [18], which mainly focused on statistical signal analysis and threshold-based decision support, the present study introduces a supervised machine learning framework for CIoT technology selection. The proposed method uses smart meter location and RSRP as input features, evaluates three supervised learning algorithms, and applies spatial holdout validation to assess model generalization in unseen deployment regions.

To address these limitations, dynamic CIoT network selection is required. This approach enables AMI devices or gateways to intelligently switch between NB-IoT and LTE-M based on real-time contextual factors, such as signal strength, latency, packet loss, device battery status, and application type. Actual energy consumption per report was not available in the current AMI field dataset. Therefore, the energy efficiency discussion is based

on the general characteristics of NB-IoT and LTE-M, while the proposed ML model itself is evaluated using location and RSRP measurements. However, manually defining rules for all these parameters is impractical and may become unreliable under changing network conditions. In this context, machine learning (ML) becomes highly relevant. ML models can learn from historical and real-time network key performance indicators (KPIs) to support adaptive and data-driven CIoT network switching decisions. Several studies have demonstrated the potential of ML for heterogeneous network access selection, particularly in IoT and smart grid applications.

For instance, in [19], probabilistic user association was formulated as a non-convex optimization problem to determine a suitable RAT between Wi-Fi and 4G technologies. However, this approach requires computationally demanding geometric methods. Similarly, in [20], matching game theory was adopted for RAT selection between LTE and Wireless Local Area Network (WLAN) technologies. Nevertheless, game-theoretic approaches are generally computationally complex, and their convergence to the optimal solution is not always guaranteed. Likewise, in [21], the authors developed a network selection scheme for resource allocation in heterogeneous networks by optimizing latency, cost, and energy consumption in a Wi-Fi/cellular network scenario. In [22], a multi-RAT mobility management algorithm was proposed, in which network topology, radio frequency (RF) conditions, and discount factors were used as parameters for RAT selection. The system was modeled as a Markov decision process (MDP) to guide the handover policy between 4G and 5G RATs. However, the study did not address radio resource management (RRM) issues and relied on an MDP-based reinforcement learning approach.

More recently, in [23], an ML-based RAT selection scheme was implemented for the Internet of Moving Things (IoMT). Four algorithms, namely Naive Bayes, multilayer perceptron, decision tree (DT), and k-nearest neighbors (KNN), were evaluated, and DT was identified as the most efficient algorithm for RAT selection. Previous RAT selection studies have mainly focused on network combinations such as 5G, 4G/Wi-Fi, or 5G/Wi-Fi. In contrast, the present study focuses on CIoT technology selection for AMI networks, specifically between NB-IoT and LTE-M. In addition, this study considers geolocation information, namely latitude and longitude, together with RSRP as input features for ML-based CIoT selection.

Recent studies have also demonstrated the usefulness of combining machine learning with spatially distributed data in energy-related applications. Moradi [24] applied k-means and hierarchical clustering together with spatial analysis to develop adaptive climate zoning for sustainable energy performance of window systems. This supports the methodological relevance of using spatial clustering and machine learning for adaptive decision-making in energy systems, which is consistent with the proposed CIoT selection framework for AMI networks.

In this research, we propose a machine learning-based framework for CIoT technology selection in AMI networks, as shown in Figure 2 (graphical illustration generated with the assistance of ChatGPT).

The proposed approach utilizes empirical field measurement data, including spatial coordinates and signal strength indicators, to predict the most suitable communication technology. Three supervised learning algorithms, namely Decision Tree, Support Vector Machine, and Extreme Gradient Boosting, are employed and evaluated. To ensure realistic performance assessment, spatial holdout validation based on spatial clustering is adopted. The proposed framework aims to improve decision accuracy, enhance adaptability, and provide a scalable solution for intelligent communication technology selection in smart grid environments.

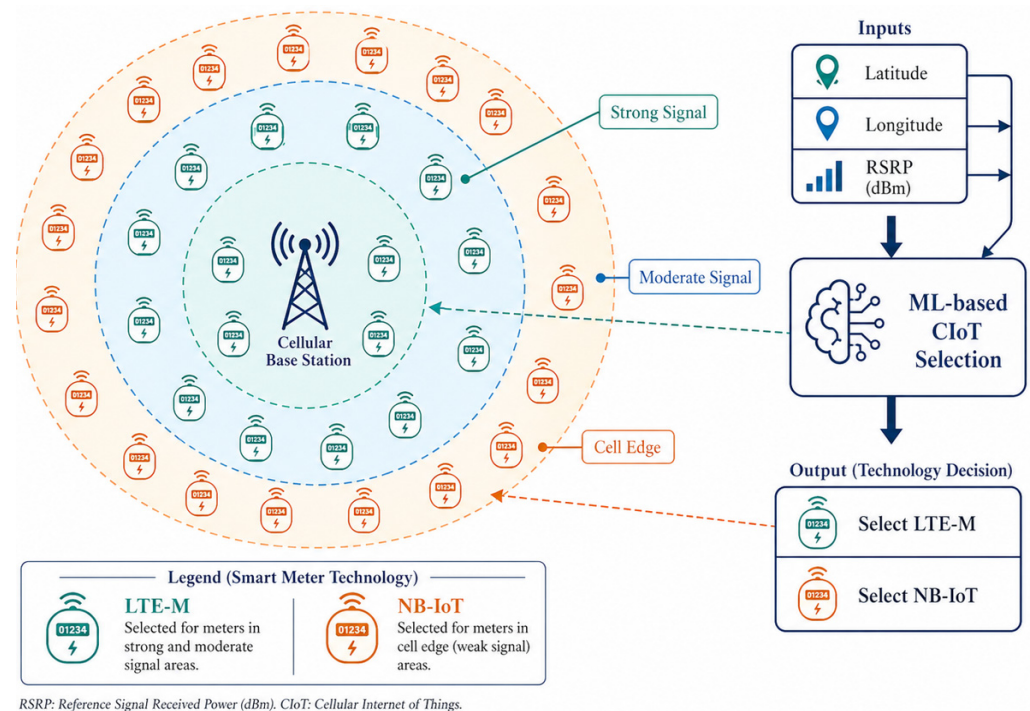


Figure 2. Spatially Varying Radio Conditions and ML-based CIoT Selection.

The main contributions of this study are summarized as follows:

- A machine learning-based CIoT technology selection framework is proposed for AMI networks, specifically focusing on NB-IoT and LTE-M selection.
- Field measurement data from AMI smart meter deployments are used to train and evaluate the proposed framework.
- Spatial clustering and spatial holdout validation are applied to reduce spatial data leakage and evaluate model generalization in unseen geographical regions.
- Three supervised learning algorithms, namely Decision Tree, SVM, and XGBoost, are compared under imbalanced CIoT class distributions.
- The results demonstrate that model performance depends on deployment area characteristics, spatial distribution, and the number of NB-IoT samples.

2. Machine Learning for CIoT

2.1. Learning-Based CIoT Network Selection

In AMI networks, smart meters are commonly deployed across heterogeneous radio environments, including dense urban areas, suburban neighborhoods, and rural regions. Although NB-IoT and LTE-M are both standardized CIoT technologies, their suitability depends on local radio conditions, service requirements, and deployment constraints. A fixed technology assignment may be sufficient when radio conditions are stable; however, in practical AMI deployments, the measured signal quality can vary substantially across meter locations. Therefore, CIoT network selection can be formulated as a supervised learning problem in which a machine learning model learns the mapping between measurable radio and spatial features and the most suitable communication technology.

In Equation (1), let D denote a dataset containing N smart meter observations. Each observation consists of an input feature vector x_i and a corresponding CIoT technology label y_i . In this study, the input vector in Equation (2) is constructed from the geographic

coordinates of each smart meter and its measured RSRP. The label represents the selected CIoT technology, namely LTE-M or NB-IoT. The dataset can be expressed as follows:

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (1)$$

$$x_i = [\text{Lat}_i, \text{Lon}_i, \text{RSRP}_i]^T \quad (2)$$

$$y_i \in \{0, 1\}, \quad (3)$$

where Lat and Lon denote the latitude and longitude of the i th smart meter, respectively, RSRP_i denotes the average received signal strength, $y_i = 0$ represents LTE-M, and $y_i = 1$ represents NB-IoT in Equation (3). The objective of the learning model in Equation (4) is to estimate a decision function that predicts the CIoT technology from the input features:

$$\hat{y}_i = f(x_i) \quad (4)$$

The model parameters are optimized by minimizing the empirical classification loss over the training dataset in Equation (5). In a general form, this optimization problem is given by:

$$\theta^* = \arg \min_{\theta} \left[\frac{1}{N} \sum_{i=1}^N L(y_i, f_{\theta}(x_i)) + \Omega(\theta) \right] \quad (5)$$

where θ represents the model parameters, $L(\cdot)$ is the classification loss function, and $\Omega(\theta)$ is a regularization term used to control model complexity and reduce overfitting. This formulation enables the model to learn nonlinear relationships between radio conditions, spatial deployment characteristics, and CIoT technology selection outcomes.

Based on this formulation, three supervised learning algorithms are selected for comparative evaluation. The selection of Decision Tree (DT), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost) is aligned with the characteristics of the proposed CIoT technology selection problem in AMI networks. The available dataset consists of structured field measurement variables, including smart meter location and RSRP, and the target output is a binary technology selection between LTE-M and NB-IoT. DT is adopted as a transparent and low-complexity baseline because its rule-based structure is suitable for explaining how radio and spatial features influence technology selection. SVM is considered to evaluate the effectiveness of margin-based classification in separating LTE-M and NB-IoT classes, particularly when the decision boundary is nonlinear and the dataset size is limited. XGBoost is included as a high-performance ensemble method capable of learning complex feature interactions and improving classification robustness under imbalanced and spatially heterogeneous conditions. These three algorithms were selected to represent different levels of model complexity and interpretability, ranging from simple rule-based learning to nonlinear margin-based classification and ensemble boosting. This comparison provides a practical and balanced evaluation framework for determining whether ML-based CIoT selection can improve AMI communication reliability compared with conventional fixed-threshold approaches.

2.2. Decision Tree Classifier

A Decision Tree (DT) is an interpretable supervised learning model that partitions the feature space into a set of decision regions. In CIoT technology selection, a DT can learn rule-based boundaries from the input features, for example, whether a particular range of RSRP values or a specific spatial region is associated with LTE-M or NB-IoT. This characteristic is particularly useful for AMI applications because the resulting decision rules are relatively easy to interpret and can be implemented in resource-constrained systems.

At each internal node of the tree, the algorithm selects a feature and a threshold that best separates the classes. A common splitting criterion is the Gini impurity, which measures the probability of misclassification within a node. For a node t containing samples from K classes. In Equation (6), the Gini impurity is defined as:

$$\text{Gini}(t) = 1 - \sum_{k=1}^K p_{k,t}^2 \quad (6)$$

where p_k is the proportion of samples belonging to class k at node t . The optimal split is selected by maximizing the impurity reduction between the parent node and its child nodes. This reduction can be expressed as:

$$\Delta\text{Gini} = \text{Gini}(t) - \left(\frac{n_L}{n} \text{Gini}(t_L) + \frac{n_R}{n} \text{Gini}(t_R) \right) \quad (7)$$

where n is the number of samples in the parent node, and n_L and n_R are the numbers of samples in the left and right child nodes, respectively. For the proposed CIoT selection problem, the DT model provides a transparent baseline that reveals how RSRP and spatial features contribute to the classification of LTE-M and NB-IoT. However, a single decision tree may be sensitive to noise and can overfit the training data if the tree depth is not properly constrained.

2.3. Support Vector Machine Classifier

Support Vector Machine (SVM) is a margin-based classification algorithm that aims to find an optimal separating hyperplane between classes. In the context of CIoT network selection, SVM attempts to determine a decision boundary between LTE-M and NB-IoT based on the input feature vector. The fundamental principle of SVM is to maximize the margin between the nearest samples of different classes, which are known as support vectors.

For a binary classification problem with y_i in $\{-1, +1\}$, the linear SVM optimization problem can be formulated as:

$$\min_{w,b,\xi} \left(\frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i \right) \quad (8)$$

subject to

$$y_i (w^T x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \quad (9)$$

where w is the weight vector, b is the bias term, ξ_i is a slack variable that allows misclassification, and C is a penalty parameter that controls the trade-off between margin maximization and classification error. For nonlinear classification, the kernel function maps the original feature space into a higher-dimensional space. In this study, the radial basis function (RBF) kernel is considered because it can capture nonlinear decision boundaries:

$$K(x_i, x_j) = e^{(-\gamma \|x_i - x_j\|^2)} \quad (10)$$

where γ controls the influence of each training sample. Since SVM is sensitive to the scale of input variables, standardization is required before model training. This is especially important when combining geographic coordinates and RSRP values, which have different numerical ranges. Although SVM can provide strong classification performance in well-separated datasets, it may be sensitive to class imbalance. Therefore, class weighting is applied in this study to reduce bias toward the dominant LTE-M class and improve the prediction of the minority NB-IoT class.

2.4. Extreme Gradient Boosting Classifier

Extreme Gradient Boosting (XGBoost) is an ensemble learning algorithm based on gradient-boosted decision trees. Unlike a single DT, XGBoost constructs multiple weak learners sequentially, where each new tree attempts to correct the residual errors of the previous ensemble. This property makes XGBoost effective for tabular datasets and nonlinear classification problems, including CIIoT technology selection using radio and spatial features.

The prediction of an XGBoost model is obtained by summing the outputs of M regression or classification trees:

$$\hat{y}_i = \sum_{m=1}^M f_m(x_i), f_m \in F \quad (11)$$

where F denotes the space of decision trees and f_m is the m th tree. The objective function of XGBoost combines the training loss with a regularization term that penalizes model complexity:

$$\text{Obj} = \sum_{i=1}^N L(y_i, \hat{y}_i) + \sum_{m=1}^M \Omega(f_m) \quad (12)$$

The regularization term for each tree can be written as:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (13)$$

where T is the number of leaves in the tree, w_j is the score of leaf j , and γ and λ are regularization parameters. By incorporating regularization and sequential error correction, XGBoost can improve predictive accuracy while reducing overfitting. In this study, XGBoost is expected to be well suited for CIIoT technology selection because it can model nonlinear relationships between RSRP, spatial location, and the selected communication technology. In addition, the class imbalance between LTE-M and NB-IoT can be addressed using the scale positive weight parameter, which increases the importance of minority-class samples during training.

2.5. Spatial Learning and Model Evaluation

A key characteristic of AMI field measurements is their spatial dependence. Smart meters located close to each other may experience similar propagation conditions, interference levels, and network coverage characteristics. If training and testing samples are randomly selected at the row level, nearby meters may appear in both sets, leading to spatial data leakage and overly optimistic performance results. To address this issue, this study applies spatial clustering based on smart meter coordinates before model evaluation.

The spatial clustering process groups smart meters according to their latitude and longitude using the k -means algorithm. For a set of coordinate vectors x_i the k -means objective function is expressed as:

$$J = \sum_{i=1}^N \sum_{k=1}^K r_{ik} \|x_i - \mu_k\|^2 \quad (14)$$

where μ_k is the centroid of cluster k , K is the number of clusters, and r_{ik} is equal to 1 if sample i is assigned to cluster k , and 0 otherwise. One spatial cluster is reserved as a holdout region, while the remaining clusters are used for training. This strategy evaluates the ability of the model to generalize to an unseen geographic region, which is more realistic than conventional random splitting for AMI deployments.

In addition to spatial holdout validation is employed by treating spatial clusters as grouping variables. This prevents samples from the same cluster from appearing simultaneously in the training and validation sets. Model performance is evaluated using four standard classification metrics: accuracy, precision, recall, and F1-score. These metrics are selected to maintain consistency with the evaluation framework used in this study and to provide a clear comparison among the considered machine learning algorithms.

Accuracy measures the overall proportion of correct predictions among all test samples and is defined as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (15)$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. In this study, the positive class is defined as NB-IoT, while LTE-M is treated as the negative class.

Precision measures the proportion of correctly predicted NB-IoT samples among all samples predicted as NB-IoT. It is defined as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (16)$$

Recall measures the proportion of actual NB-IoT samples that are correctly identified by the model. It is expressed as:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (17)$$

The F1-score provides the harmonic mean of precision and recall, thereby balancing the ability of the model to avoid false NB-IoT predictions and to correctly identify actual NB-IoT samples:

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (18)$$

The overall ML-based CIoT selection workflow implemented in this study consists of data loading, label encoding, spatial clustering, spatial holdout separation, model training, and final performance comparison. Decision Tree, SVM, and XGBoost are selected to represent interpretable rule-based learning, margin-based classification, and ensemble boosting, respectively. This theoretical framework provides the basis for the subsequent measurement setup and methodology sections, where empirical AMI field data are used to evaluate the feasibility of adaptive CIoT technology selection between LTE-M and NB-IoT.

3. Materials and Methods

3.1. Dataset Description

This study uses smart meter field measurement data to develop a machine learning-based CIoT technology selection model for AMI networks. Each row of the dataset represents one smart meter observation. The input features consist of the geographical coordinates of the smart meter and the measured radio signal strength. Specifically, the dataset includes Meter_ID, Latitude, Longitude, RSRP_mean, and Selected_CIoT. The Meter_ID is used to identify each smart meter, while Latitude and Longitude represent the spatial location of the device. The RSRP_mean denotes the average Reference Signal Received Power obtained from field measurements. The Selected_CIoT column represents the communication technology assigned to each smart meter, namely LTE-M or NB-IoT. A summary of the dataset variables and their descriptions is presented in Table 1.

Table 1. Dataset structure used for CIoT technology selection.

Variable	Description
Meter_ID	Unique identifier of each smart meter
Latitude	Geographic latitude of the smart meter
Longitude	Geographic longitude of the smart meter
RSRP_mean	Average Reference Signal Received Power
Selected_CIoT	Selected CIoT technology, LTE-M or NB-IoT

The Selected_CIoT label represents the CIoT technology assigned to each smart meter in the AMI dataset. In the field deployment, LTE-M was generally configured for smart meters with sufficient radio conditions, while NB-IoT was assigned to smart meters requiring extended coverage or more robust connectivity under weaker signal conditions. Therefore, the label reflects the deployment and engineering selection outcome available in the AMI field records. It should be noted that both LTE-M and NB-IoT were not independently tested at every measurement point. Accordingly, the proposed model is designed as an RSRP-and-location-based CIoT classification framework rather than a complete QoS optimization model.

The input feature vector for the i -th smart meter is defined as:

$$\mathbf{x}_i = [\text{Lat}_i, \text{Lon}_i, \text{RSRP}_i]^T \quad (19)$$

where Lat_i , Lon_i , and RSRP_i denote the latitude, longitude, and average RSRP of the i -th smart meter, respectively. The objective of the model is to predict the selected CIoT technology from these input features.

Only latitude, longitude, and RSRP_mean were used as input features because these parameters were consistently available for all smart meter observations in the field dataset. Other radio and network KPIs, such as SINR, RSRQ, latency, packet delivery ratio, retransmission behavior, and energy consumption per report, were not consistently available for all samples. Therefore, the scope of this study is limited to RSRP-and-location-based CIoT classification.

3.2. Data Preprocessing and Label Encoding

Before model training, the dataset is preprocessed to ensure consistency and reliability. Records with missing values in latitude, longitude, RSRP, or CIoT technology labels are removed. The numerical features are converted into appropriate numerical formats, and the CIoT technology labels are standardized to ensure consistent naming between LTE-M and NB-IoT.

For machine learning implementation, the categorical label Selected_CIoT is encoded into binary numerical values. LTE-M is encoded as 0, while NB-IoT is encoded as 1. This encoding allows the selected algorithms to perform binary classification and enables consistent calculation of the confusion matrix and evaluation metrics. In addition, feature standardization is applied for the Support Vector Machine model because SVM is sensitive to the numerical scale of input variables. The standardization process is fitted only on the training data and then applied to the test data to prevent data leakage.

3.3. Spatial Clustering and Holdout Region Selection

Since AMI field measurements are spatially dependent, smart meters located close to one another may experience similar propagation conditions, interference levels, and network coverage characteristics. Therefore, random row-level splitting may lead to spatial data leakage, where nearby smart meters appear in both the training and testing sets. This can result in overly optimistic model performance.

To address this issue, this study applies spatial clustering based on the geographical coordinates of smart meters. The k-means algorithm is used to group smart meters into spatial clusters using latitude and longitude as clustering inputs. After clustering, one spatial cluster is selected as the holdout region, while the remaining clusters are used for model training. The holdout region represents an unseen geographical area and is used to evaluate the ability of the trained model to generalize to a new deployment region.

In cases where NB-IoT samples are limited, the holdout selection process prioritizes retaining both LTE-M and NB-IoT samples in the training set to ensure that the model can learn both classes. When possible, a holdout cluster containing NB-IoT samples is selected to allow the minority class to be evaluated in the test region.

3.4. Machine Learning Pipeline

Three supervised machine learning algorithms are implemented and compared in this study: Decision Tree (DT), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost). These algorithms are selected to represent different learning characteristics. DT provides an interpretable rule-based baseline, SVM represents a margin-based classifier capable of nonlinear classification through kernel functions, and XGBoost represents an ensemble boosting approach suitable for structured tabular data.

The machine learning pipeline consists of data loading, data cleaning, label encoding, spatial clustering, spatial holdout separation, model training, prediction, and final performance comparison. For DT and XGBoost, the input features are directly used for model training. For SVM, feature standardization is included in the pipeline before classification. Class weighting is applied where appropriate to reduce the bias toward the dominant LTE-M class and improve the prediction of the minority NB-IoT class.

Group-aware cross-validation is also employed by treating the spatial clusters as grouping variables. This ensures that samples from the same spatial cluster do not appear simultaneously in the training and validation sets. Therefore, the evaluation better reflects model robustness under spatially separated deployment conditions.

3.5. Performance Evaluation Metrics

The performance of the proposed CIoT technology selection models is evaluated using four standard classification metrics: accuracy, precision, recall, and F1-score. These metrics are selected to be consistent with the evaluation framework used in the study and to provide a clear comparison among DT, SVM, and XGBoost.

3.6. Proposed ML-Based CIoT Selection Workflow

The overall workflow of the proposed machine learning-based CIoT technology selection framework is illustrated in Figure 3 (graphical illustration generated with the assistance of ChatGPT). The workflow begins with the collection of AMI field measurement data from smart meters. The input dataset consists of smart meter identifiers, geographical coordinates, average RSRP values, and selected CIoT technology labels. These data are used as the basis for developing a supervised learning model to classify the appropriate communication technology between LTE-M and NB-IoT.

The second stage involves data preprocessing and label encoding. In this stage, incomplete records are removed, numerical features are converted into suitable formats, and CIoT technology labels are standardized. The categorical labels are then encoded into binary classes, where LTE-M is represented as 0 and NB-IoT is represented as 1. This encoding enables the machine learning algorithms to perform binary classification.

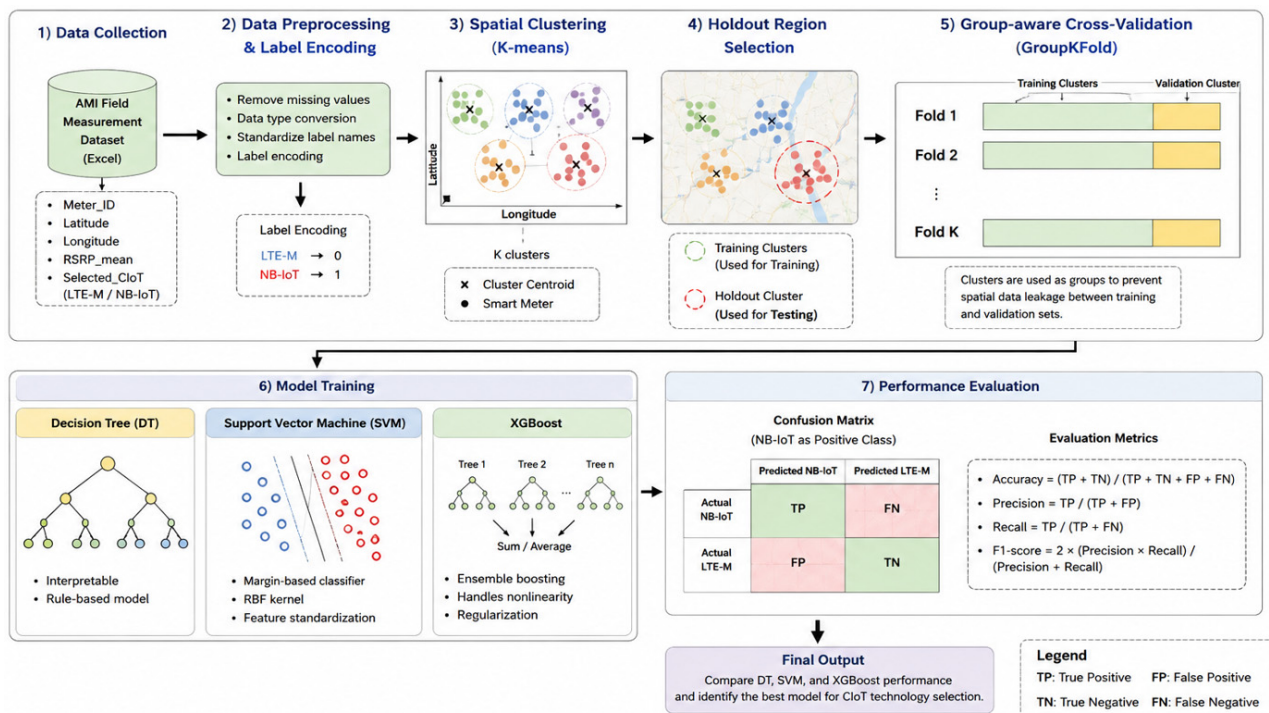


Figure 3. Proposed machine learning-based CIoT technology selection workflow for AMI networks.

Next, spatial clustering is applied using the k-means algorithm based on the latitude and longitude of the smart meters. This step groups nearby smart meters into spatial clusters, reflecting the spatial dependency of AMI field measurements. One cluster is selected as the holdout region for testing, while the remaining clusters are used for training. This spatial holdout strategy is adopted to evaluate model generalization on an unseen geographical area and to reduce spatial data leakage.

In addition to the holdout region is applied by treating spatial clusters as grouping variables. This prevents smart meters from the same cluster from appearing simultaneously in the training and validation sets. As a result, the evaluation provides a more realistic assessment of model robustness under spatially separated AMI deployment conditions. The holdout region was selected using predefined criteria rather than random assignment. The training set was required to contain both LTE-M and NB-IoT samples. When possible, the holdout cluster was also required to contain NB-IoT samples to allow evaluation of minority-class detection. Among feasible clusters, the cluster with a size closest to approximately 30% of the dataset was selected as the holdout region.

The model training stage evaluates three supervised learning algorithms, namely Decision Tree, Support Vector Machine, and XGBoost. Decision Tree is used as an interpretable rule-based model, SVM represents a margin-based classifier with feature standardization, and XGBoost represents an ensemble boosting approach capable of handling nonlinear relationships in tabular data. Finally, model performance is assessed using the confusion matrix and four evaluation metrics: accuracy, precision, recall, and F1-score. The final output compares the performance of the three algorithms and identifies the most suitable model for CIoT technology selection in AMI networks.

4. Experimental Setup

4.1. Field Measurement Areas

The experimental evaluation was conducted using two AMI field measurement areas. Each area consisted of smart meters deployed within the coverage of a cellular base station

supporting CIoT communication. The smart meters were geographically distributed within the service area and were configured to communicate using either LTE-M or NB-IoT. The purpose of using two field areas was to evaluate the capability of the proposed machine learning-based CIoT selection framework under different spatial distributions and signal strength conditions.

The first field area, referred to as Area 1, consisted of 96 smart meter observations. Among these observations, 80 smart meters were labeled as LTE-M and 16 smart meters were labeled as NB-IoT. The measured average RSRP values ranged from -108.12 dBm to -65.09 dBm, with an average value of -84.57 dBm. The spatial distribution of the smart meters in Area 1 and the corresponding holdout region are shown in Figure 4.

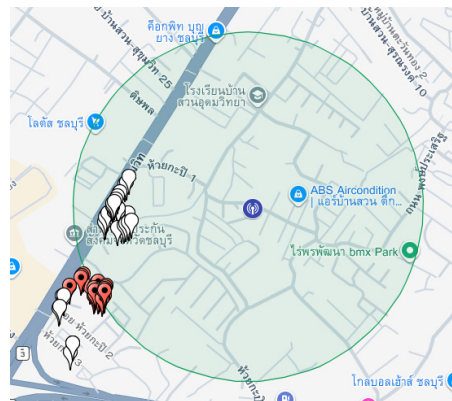


Figure 4. Spatial distribution of smart meters (white-colored marker) and holdout region (red-colored marker) in Area 1.

The second field area, referred to as Area 2, consisted of 349 smart meter observations. In this area, 276 smart meters were labeled as LTE-M and 73 smart meters were labeled as NB-IoT. The measured average RSRP values ranged from -108.35 dBm to -73.00 dBm, with an average value of -87.61 dBm. The spatial distribution of the smart meters in Area 2 and the corresponding holdout region are shown in Figure 5.

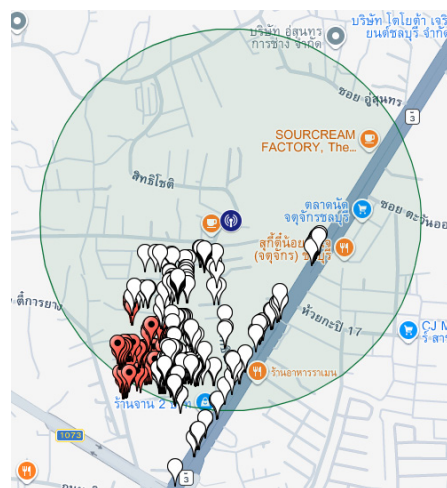


Figure 5. Spatial distribution of smart meters (white-colored marker) and holdout region (red-colored marker) in Area 2.

4.2. Dataset Configuration

The dataset for each area was prepared in spreadsheet format, where each row represents one smart meter. The input variables consisted of Meter_ID, Latitude, Longitude, RSRP_mean, and Selected_CIoT. The Meter_ID was used as the unique identifier of each

smart meter, while Latitude and Longitude represented the geographical position of the device. The RSRP_mean value represented the average received signal strength, and Selected_CIoT represented the target label, either LTE-M or NB-IoT.

For model implementation, the Selected_CIoT label was encoded as a binary variable, where LTE-M was assigned a value of 0 and NB-IoT was assigned a value of 1. The input feature vector used for training and testing was composed of latitude, longitude, and RSRP_mean. This configuration enables the model to learn the relationship between spatial location, signal strength, and the selected CIoT communication technology.

A summary of the datasets used in the experimental setup is provided in Table 2.

Table 2. Summary of field measurement datasets.

Area	Total Smart Meters	LTE-M Samples	NB-IoT Samples	RSRP Range (dBm)	Mean RSRP (dBm)
Area 1	96	80	16	−108.12 to −65.09	−84.57
Area 2	349	276	73	−108.35 to −73.00	−87.61

4.3. Spatial Holdout Configuration

To avoid spatial data leakage, the experimental setup did not use conventional random row-level splitting. Instead, spatial clustering was applied to the smart meter coordinates using the k-means algorithm. The latitude and longitude of each smart meter were used to form spatial clusters. These clusters were then used to separate the dataset into training and testing subsets.

For each area, one spatial cluster was selected as the holdout region, while the remaining clusters were used for model training. The holdout region represents an unseen geographical area and was used to evaluate the generalization capability of the trained model. This spatial holdout strategy is more realistic for AMI deployments because smart meters located close to one another may experience similar radio propagation and network coverage conditions.

In this study, four spatial clusters were generated for each area. The purpose of k-means clustering was not to identify the optimal number of natural geographical zones, but to create spatially separated regions for model evaluation. The value $k = 4$ provided a practical balance between cluster size, spatial separation, and class representation. In particular, it produced a holdout region close to approximately 30% of the dataset while retaining both LTE-M and NB-IoT samples in the training data. The holdout cluster was selected based on three criteria: ensuring that the training set contained NB-IoT samples, selecting a test cluster containing NB-IoT samples where possible, and keeping the test size close to 30% of the dataset. For Area 1, the selected holdout cluster contained 35 smart meters, consisting of 27 LTE-M samples and 8 NB-IoT samples. The remaining 61 smart meters were used for training, consisting of 53 LTE-M samples and 8 NB-IoT samples. For Area 2, the selected holdout cluster contained 112 smart meters, consisting of 87 LTE-M samples and 25 NB-IoT samples. The remaining 237 smart meters were used for training, consisting of 189 LTE-M samples and 48 NB-IoT samples. The spatial holdout configuration is summarized in Table 3.

Table 3. Spatial holdout configuration for Area 1 and Area 2.

Area	Training Samples	Training LTE-M	Training NB-IoT	Test Samples	Test LTE-M	Test NB-IoT
Area 1	61	53	8	35	27	8
Area 2	237	189	48	112	87	25

4.4. Machine Learning Implementation

Three supervised machine learning algorithms were implemented and evaluated: Decision Tree, Support Vector Machine, and Extreme Gradient Boosting. These models were selected to represent three different learning characteristics. The Decision Tree model was used as an interpretable rule-based classifier. The SVM model was used to evaluate margin-based nonlinear classification using an RBF kernel. XGBoost was used as an ensemble learning model suitable for structured tabular datasets and nonlinear feature interactions.

The machine learning implementation was performed using Python-3 in Google Colab. The main libraries included pandas for data handling, scikit-learn for preprocessing, clustering, classification, and evaluation, and XGBoost for gradient boosting classification. The model input features were latitude, longitude, and RSRP_mean. For SVM, feature standardization was applied before model training because SVM is sensitive to the scale of input variables. For Decision Tree and XGBoost, the original feature values were used directly.

To reduce the effect of class imbalance between LTE-M and NB-IoT samples, class weighting was applied where appropriate. In particular, the Decision Tree and SVM models were configured with balanced class weights, while XGBoost used a positive class weighting factor derived from the ratio between LTE-M and NB-IoT samples in the training set. This configuration aimed to reduce bias toward the dominant LTE-M class and improve the prediction of the minority NB-IoT class.

The main hyperparameters of the three algorithms were configured as follows. The Decision Tree model used balanced class weights and a minimum samples leaf value of 3. The SVM model used an RBF kernel with $C = 10.0$, $\gamma = \text{scale}$, and balanced class weights. XGBoost used 300 estimators, a maximum depth of 5, a learning rate of 0.05, subsampling of 0.9, column sampling of 0.9, and a regularization parameter of 1.0. The positive class weighting factor was calculated from the ratio of LTE-M to NB-IoT samples in the training set.

4.5. Performance Evaluation

The performance of each machine learning model was evaluated using four classification metrics: accuracy, precision, recall, and F1-score. NB-IoT was treated as the positive class, while LTE-M was treated as the negative class. Accuracy measures the overall proportion of correctly classified samples. Precision evaluates how many samples predicted as NB-IoT were actually NB-IoT. Recall measures how many actual NB-IoT samples were correctly identified. The F1-score provides the harmonic mean of precision and recall and is particularly useful when the dataset contains an imbalanced distribution between LTE-M and NB-IoT samples.

5. Results and Discussion

5.1. Spatial Holdout Analysis

The experimental results were evaluated using the spatial holdout strategy described in Section 4. Unlike conventional random splitting, this approach reserves one spatial cluster as an unseen test region while using the remaining clusters for training. This evaluation setting is more suitable for AMI deployment because smart meters located close to each other may experience similar radio propagation and network coverage conditions.

For Area 1, the dataset contained 96 smart meter observations, consisting of 80 LTE-M samples and 16 NB-IoT samples. After spatial clustering, the selected holdout region contained 35 smart meters, including 27 LTE-M samples and 8 NB-IoT samples. The remaining 61 samples were used for training, consisting of 53 LTE-M samples and 8 NB-IoT

samples. This configuration ensured that both LTE-M and NB-IoT classes were present in both the training and testing subsets.

For Area 2, the dataset contained 349 smart meter observations, consisting of 276 LTE-M samples and 73 NB-IoT samples. The selected holdout region contained 112 smart meters, including 87 LTE-M samples and 25 NB-IoT samples. The remaining 237 samples were used for training, consisting of 189 LTE-M samples and 48 NB-IoT samples. Compared with Area 1, Area 2 provided a larger dataset and a wider spatial distribution, which enabled a more representative assessment of the proposed machine learning-based CIoT selection framework.

The spatial holdout results indicate that both areas exhibit class imbalance, where LTE-M is the dominant class and NB-IoT is the minority class. This condition reflects realistic AMI deployment scenarios, where most smart meters may operate under sufficient LTE-M coverage, while a smaller number of devices located in weaker signal regions may require NB-IoT connectivity.

5.2. Classification Performance in Area 1

The classification performance of Decision Tree, Support Vector Machine, and XGBoost in Area 1 is presented in Table 4. NB-IoT was treated as the positive class, while LTE-M was treated as the negative class.

Table 4. Classification performance comparison of machine learning algorithms in Area 1.

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.7143	0.4444	1.0000	0.6154
SVM	0.5429	0.3333	1.0000	0.5000
XGBoost	0.5143	0.3200	1.0000	0.4848

The results show that all three models were able to identify all NB-IoT samples in the holdout region, as indicated by the recall value of 1.0000. This means that no actual NB-IoT sample was misclassified as LTE-M in Area 1. However, the precision values were relatively low for all models, indicating that several LTE-M samples were incorrectly classified as NB-IoT.

Among the three algorithms, Decision Tree achieved the highest accuracy of 0.7143 and the highest F1-score of 0.6154. This result suggests that the rule-based structure of Decision Tree was effective in capturing the relationship between RSRP, spatial location, and CIoT technology selection in Area 1. The confusion matrix of Decision Tree showed 17 correctly classified LTE-M samples, 10 LTE-M samples misclassified as NB-IoT, and all 8 NB-IoT samples correctly identified.

SVM achieved an accuracy of 0.5429 and an F1-score of 0.5000. Although SVM achieved perfect recall, its precision was lower than that of Decision Tree, indicating a higher number of false NB-IoT predictions. XGBoost achieved an accuracy of 0.5143 and an F1-score of 0.4848. Although XGBoost is generally effective for nonlinear tabular data, its lower performance in Area 1 may be attributed to the limited number of NB-IoT samples available in the training set. Overall, Decision Tree provided the best performance in Area 1, particularly in terms of accuracy and F1-score.

The Area 1 results should be interpreted with caution because the dataset contains only 96 observations and 16 NB-IoT samples. This limited sample size may reduce statistical stability and make the results more sensitive to the selected spatial holdout region. Therefore, although Decision Tree achieved the best performance in Area 1, additional validation using larger datasets and repeated spatial holdout experiments is required to confirm the robustness of this finding.

5.3. Classification Performance in Area 2

The classification performance of the three machine learning algorithms in Area 2 is summarized in Table 5. Area 2 contains a larger number of smart meter samples than Area 1 and provides a more comprehensive spatial distribution for evaluating model generalization.

Table 5. Classification performance comparison of machine learning algorithms in Area 2.

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	0.8482	0.9000	0.3600	0.5143
SVM	0.9286	0.9474	0.7200	0.8182
XGBoost	0.9732	0.9583	0.9200	0.9388

The results indicate that XGBoost achieved the highest overall performance in Area 2, with an accuracy of 0.9732, precision of 0.9583, recall of 0.9200, and F1-score of 0.9388. The confusion matrix shows that XGBoost correctly classified 86 LTE-M samples and 23 NB-IoT samples in the holdout region, while only one LTE-M sample was misclassified as NB-IoT and two NB-IoT samples were misclassified as LTE-M. The high precision value indicates that most samples predicted as NB-IoT by XGBoost were correctly classified. In addition, the high recall value demonstrates that XGBoost was able to identify most actual NB-IoT samples in the spatial holdout region. Therefore, XGBoost provided the best balance between minimizing false NB-IoT predictions and detecting actual NB-IoT samples.

SVM achieved the second-best performance, with an accuracy of 0.9286, precision of 0.9474, recall of 0.7200, and F1-score of 0.8182. The model correctly classified 86 LTE-M samples and 18 NB-IoT samples, while one LTE-M sample was incorrectly predicted as NB-IoT and seven NB-IoT samples were misclassified as LTE-M. Compared with Decision Tree, SVM provided substantially better recall and F1-score, indicating that the margin-based classifier was able to detect a larger proportion of NB-IoT samples when the class distribution in the holdout region was improved.

Decision Tree achieved an accuracy of 0.8482, precision of 0.9000, recall of 0.3600, and F1-score of 0.5143. The model correctly classified 86 LTE-M samples and 9 NB-IoT samples, while one LTE-M sample was misclassified as NB-IoT and 16 NB-IoT samples were misclassified as LTE-M. Although Decision Tree achieved high precision, its recall was considerably lower than those of SVM and XGBoost. This indicates that Decision Tree was conservative in predicting NB-IoT and had a reduced ability to identify NB-IoT samples in the spatial holdout region.

Due to the imbalanced distribution between LTE-M and NB-IoT samples, the results should not be interpreted using accuracy or F1-score alone. Therefore, precision, recall, F1-score, and confusion matrix results were considered together. Since NB-IoT is treated as the positive class, recall is used to indicate the ability of each model to detect actual NB-IoT samples, while precision indicates the reliability of NB-IoT predictions. This combined interpretation reduces the risk of misleading conclusions under imbalanced class conditions.

The different model behaviors across the two areas indicate that the spatial distribution and class balance strongly influence CIoT classification performance. In Area 1, all models detected the NB-IoT samples but also produced several false NB-IoT predictions, leading to lower precision. This suggests that the smaller dataset may not provide sufficient information for more complex nonlinear models. In Area 2, XGBoost achieved the best performance, indicating that the ensemble boosting approach was more effective in

capturing nonlinear relationships among location, RSRP, and CIoT technology selection in a larger dataset.

The current dataset is limited to two AMI deployment areas and contains an imbalanced number of LTE-M and NB-IoT samples. This reflects practical AMI deployment conditions, where NB-IoT is generally required for a smaller number of meters located in weak signal or extended coverage regions. However, the limited number of NB-IoT samples may affect model generalization and increase the risk of overfitting, especially in smaller datasets. Therefore, future work will include larger and more balanced datasets collected from additional deployment areas, operators, and radio environments.

6. Conclusions

This paper proposed a machine learning-based framework for CIoT technology selection in AMI networks using smart meter location and RSRP measurements as input features. Three supervised learning algorithms, namely Decision Tree, Support Vector Machine, and XGBoost, were evaluated under a spatial holdout strategy to assess their ability to classify the appropriate communication technology between LTE-M and NB-IoT in unseen geographical regions. The results from two field measurement areas show that the classification performance depends strongly on the spatial distribution of smart meters, the number of training samples, and the imbalance between LTE-M and NB-IoT classes. In Area 1, which consisted of 96 smart meter observations, Decision Tree achieved the best overall performance, with an accuracy of 0.7143 and an F1-score of 0.6154. All three models achieved a recall of 1.0000 for NB-IoT in Area 1, indicating that all NB-IoT samples in the holdout region were correctly identified. However, the relatively low precision values indicate that several LTE-M samples were misclassified as NB-IoT.

In Area 2, which consisted of 349 smart meter observations, XGBoost achieved the best performance among the three algorithms, with an accuracy of 0.9732, precision of 0.9583, recall of 0.9200, and F1-score of 0.9388. SVM achieved the second-best performance, with an accuracy of 0.9286 and an F1-score of 0.8182, while Decision Tree achieved an accuracy of 0.8482 and an F1-score of 0.5143. These results indicate that XGBoost was more effective in capturing nonlinear relationships among latitude, longitude, and RSRP in a larger and more spatially heterogeneous dataset. The findings also confirm that accuracy alone is insufficient for evaluating CIoT selection performance under imbalanced data conditions, since recall and F1-score are essential for assessing the ability of a model to detect the minority NB-IoT class. Overall, the proposed framework demonstrates the feasibility of ML-based adaptive CIoT technology selection for AMI networks. Decision Tree may be suitable for smaller datasets where interpretability is important, whereas XGBoost is more appropriate for larger and more complex deployment areas. Future work will incorporate additional radio and network indicators, such as RSRQ, SINR, latency, packet delivery ratio, and retransmission behavior, to further improve model robustness and support large-scale AMI deployment.

From a practical deployment perspective, the proposed ML model can be implemented at the AMI head-end system, utility cloud platform, or gateway management system rather than directly inside each smart meter. Since the model uses only latitude, longitude, and RSRP as input features, the inference process is computationally lightweight and can be used for batch-based CIoT configuration support. The output of the model can assist utility engineers in selecting LTE-M or NB-IoT during smart meter commissioning, network optimization, or maintenance planning.

Overall, the proposed framework demonstrates the feasibility of using machine learning to support RSRP-and-location-based CIoT technology selection in AMI networks.

However, the current study should be interpreted as an initial feasibility evaluation based on two deployment areas.

Actual energy consumption per report was not available in the current AMI field dataset. Therefore, the energy efficiency discussion is based on the general characteristics of NB-IoT and LTE-M, while the proposed ML model itself is evaluated using location and RSRP measurements. Future work will incorporate energy consumption per report and other QoS indicators to support more comprehensive CIoT technology selection.

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