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ANALYTICAL STUDY OF MACHINE LEARNING-BASED DECISION FUNCTIONS IN IOT SENSOR NETWORKS

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Abstract

The growing adoption of Internet of Things (IoT) sensor networks has necessitated the development of efficient decision-making functions to process the large volumes of data generated in real-time environments. This study presents an analytical examination of machine learning (ML)-based decision functions in IoT sensor networks, focusing on classification and regression models employed to make decisions under constrained resources such as energy, bandwidth, and processing power. Various machine learning models, including decision trees, support vector machines, and ensemble methods, are evaluated based on their performance in terms of accuracy, computational efficiency, and resource consumption. The results highlight trade-offs between model complexity and resource demands, providing insights into selecting optimal decision functions for specific IoT applications. Additionally, this study proposes a framework for selecting and implementing machine learning-based decision functions in sensor networks, ensuring high performance while maintaining resource efficiency. The findings contribute to the ongoing efforts to optimize IoT sensor networks and provide practical guidance for deploying machine learning algorithms in real-world sensor applications.

Keywords: IoT sensor networks, machine learning, decision functions, classification/regression models, ensemble learning, performance evaluation, feature selection, resource-constrained networks.

1. Introduction

1.1 Background & Motivation

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The Internet of Things (IoT) represents an ecosystem of interconnected devices and systems that collect, process, and share data through sensors embedded in physical objects. These sensors capture a wide range of environmental, physical, or operational parameters such as temperature, humidity, motion, or light intensity, facilitating the real-time monitoring of various systems[1]. The collected data is then used to derive actionable insights, optimize processes, and enhance decision-making. The ubiquitous deployment of IoT devices across multiple domains, including healthcare, agriculture, industrial automation, and smart cities, has brought about transformative changes by enabling better resource management, automation, and predictive capabilities[2]. However, this proliferation of IoT devices generates enormous volumes of data, which necessitates efficient techniques for data analysis and decision-making to ensure meaningful interpretations and actions.

One of the key challenges in IoT sensor networks lies in the design and implementation of decision-making functions that can process sensor data effectively. Decision functions, such as anomaly detection, event classification, and predictive maintenance, are integral to IoT systems. These decision functions help detect irregularities in sensor readings, classify events based on predefined criteria, and predict future trends based on historical data, all of which are essential for maintaining system reliability and efficiency[3]. For example, anomaly detection algorithms can identify faulty sensors or unusual behavior in industrial IoT networks, while predictive maintenance algorithms can foresee equipment failures, thereby preventing costly downtimes. These decision-making processes allow IoT networks to operate autonomously and efficiently, optimizing performance while reducing human intervention.

With the increasing scale and complexity of IoT systems, traditional decision-making methods often struggle to cope with the challenges of data heterogeneity, real-time processing requirements, and limited computational resources. Machine learning (ML) has emerged as a powerful tool for addressing these challenges. ML algorithms, such as classification, regression, and clustering, offer adaptive and scalable solutions for deriving decision functions from raw sensor data. Unlike rule-based systems, which rely on predefined rules and expert knowledge[4], ML algorithms can automatically learn patterns and correlations from large datasets, enabling them to make data-driven decisions in real-time. This ability to adapt to changing data distributions and learn from new sensor data makes ML an increasingly vital tool for IoT networks, especially in resource-constrained environments where computational power, memory, and energy are limited.

The integration of ML into IoT sensor networks provides significant advantages over traditional methods, particularly in dynamic and heterogeneous environments. The scalability of ML models allows them to handle the growing volume of data generated by IoT devices, while their ability to learn from complex, high-dimensional sensor data enables more accurate and context-sensitive decision-making[5]. Moreover, ML algorithms can optimize resource usage by automatically adjusting their behavior based on available resources, thus ensuring the efficiency of IoT systems even in challenging conditions.

1.2 Problem Statement

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Despite the clear advantages of ML in IoT sensor networks, several challenges remain in selecting, designing, and analyzing decision functions within these environments. IoT networks typically operate under stringent constraints, including limited energy resources, bandwidth limitations, and the need for low-latency communication. These constraints complicate the deployment of machine learning models, as many traditional ML algorithms are computationally intensive and may require substantial memory or processing power, which is often unavailable in low-power IoT devices. Furthermore, the heterogeneity of IoT sensor networks ranging from different sensor types to varying data quality and communication protocols adds another layer of complexity when designing decision functions[6]. The variation in sensor performance, reliability, and data fidelity can significantly affect the quality of decisions made by the ML models, leading to potential inefficiencies or failures in the system.

A critical gap in the existing literature is the lack of systematic and analytical studies on the performance of different decision functions in IoT sensor networks. While numerous studies have explored the application of ML in IoT contexts, most focus on empirical performance evaluations of specific algorithms without offering a comprehensive analysis of the trade-offs involved in terms of both accuracy and resource demands. Few studies have thoroughly examined how different decision functions, such as classification and regression models, perform under resource constraints, or how they can be optimized to balance performance and efficiency[7]. This lack of in-depth analysis prevents the effective deployment of ML decision functions in real-world IoT sensor networks, where both computational efficiency and decision accuracy are crucial for successful operation.

1.3 Research Objectives & Questions

The primary objective of this research is to examine the performance of machine learning-based decision functions in IoT sensor networks, specifically focusing on how different models perform under resource constraints such as energy limitations, bandwidth, and processing power. This study aims to investigate the effectiveness of various machine learning models, including classification and regression techniques, in terms of their ability to accurately make decisions while minimizing resource consumption. Furthermore, the research will compare the performance of individual models versus ensemble methods, evaluating them based on key metrics such as accuracy, computational efficiency, and latency. A significant aspect of this study is to propose a methodological framework for selecting and implementing machine learning-based decision functions in IoT sensor environments, ensuring the models are optimized for both performance and resource efficiency. The research will address critical questions, such as which machine learning decision functions provide the best trade-offs between accuracy and resource consumption in IoT sensor networks[8]. Additionally, it will explore how the characteristics of the IoT sensor network such as node density, heterogeneity, and communication latency affect the performance of machine learning decision functions. Lastly, the study will examine how varying resource constraints influence the effectiveness of different decision functions, providing insights into the design and deployment of machine learning models in real-world IoT applications.

1.4 Scope and Contributions

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This study focuses on the application of machine learning-based decision functions in wireless sensor networks (WSNs) and edge-based IoT nodes. These sensor networks are often deployed in environments with limited resources and dynamic conditions, such as smart agriculture, industrial monitoring, and healthcare systems. The study explores a variety of ML models, including decision trees, support vector machines, random forests, and ensemble learning techniques, to evaluate their suitability for real-time decision-making in IoT sensor networks. The performance of each model will be assessed based on multiple metrics, including classification/regression accuracy, energy consumption, computational requirements, and latency. The research also explores the impact of different network characteristics, such as sensor heterogeneity, data communication delay, and sensor failure, on the decision-making process. One of the primary contributions of this research is the development of a comprehensive analytical framework for selecting and implementing ML-based decision functions in resource-constrained IoT sensor networks. Unlike many empirical studies, this work provides a systematic analysis of the trade-offs between performance and resource usage, helping to identify optimal models for specific IoT applications. Additionally, this study offers practical insights and guidelines for deploying machine learning algorithms in real-world IoT sensor networks, making it a valuable resource for both researchers and practitioners in the field.

2. Literature Survey

2.1 Overview of ML in IoT Sensor Networks

Machine learning (ML) has gained significant attention in the context of Internet of Things (IoT) sensor networks due to its potential to automatically process and analyze the massive volumes of data generated by a multitude of interconnected devices[8]. IoT networks, which consist of a variety of sensors deployed to monitor real-time events or processes, generate data streams that are often high-dimensional and complex, making manual analysis impractical. Machine learning models, ranging from supervised classification algorithms to unsupervised anomaly detection techniques, have thus emerged as effective tools to process and derive actionable insights from this data[9]. A variety of ML techniques are being applied to IoT sensor networks, including but not limited to classification models, anomaly detection, clustering, and regression. These models have been utilized to solve a wide array of problems within IoT contexts, such as event classification, sensor fault detection, energy consumption prediction, and intrusion detection[10]. For instance, in smart homes or industrial IoT settings, anomaly detection techniques, such as clustering-based methods or support vector machines (SVM), are frequently used to identify irregular sensor readings indicative of malfunctioning devices or unauthorized activity. Similarly, predictive models, such as decision trees or neural networks, are applied to forecast system failures or predict environmental parameters, such as temperature or humidity, based on historical data[11]. Moreover, ML-based models are particularly valuable in the implementation of predictive maintenance systems, where models predict the remaining useful life (RUL) of machines based on sensor data, thereby preventing unnecessary maintenance and minimizing costs. Recent literature highlights the effectiveness of deep learning in extracting complex patterns from sensor data. For example, convolutional neural networks (CNNs) have been successfully applied in image-based IoT applications, such

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as surveillance or object recognition[12], while recurrent neural networks (RNNs) are employed in time-series analysis for tasks like sensor data prediction. While much of the literature focuses on specific algorithms applied to IoT sensor networks, review articles in recent years, such as those by [13)] and [14], highlight emerging trends in ML applications, including the adoption of ensemble methods and hybrid models that combine the strengths of different algorithms to improve overall decision-making accuracy and robustness in IoT networks.

2.2 Decision Functions and Their Role

In the context of machine learning, a decision function refers to a mathematical model or algorithm used to map input features to an output prediction, which can either be a class label (classification) or a continuous value (regression). The role of decision functions in IoT sensor networks is crucial, as they provide the basis for automated decision-making based on real-time sensor data. Common decision functions include logistic regression, support vector machines (SVM), decision trees, random forests, neural networks, and ensemble learning methods. Each type of model has its strengths and applications, depending on the nature of the problem and the resources available in the network[15]. Logistic regression is often used for binary classification tasks, where the goal is to distinguish between two classes based on input features, such as detecting intrusion in a network. SVMs, known for their robustness in high-dimensional spaces, are frequently employed in anomaly detection tasks within IoT sensor networks, particularly in cases where the data exhibits non-linear characteristics[16] Decision trees and random forests are widely used in sensor networks for both classification and regression tasks due to their ability to handle both categorical and continuous variables, making them versatile for various IoT applications, such as environmental monitoring or fault detection. Neural networks, including deep learning models, are gaining traction in IoT networks due to their ability to automatically extract features from raw sensor data, making them well-suited for complex tasks such as predictive maintenance or multi-class classification. Ensemble methods, such as random forests and boosting algorithms[17], are particularly useful in IoT settings where a high degree of accuracy is required, as these methods combine multiple base models to improve overall decision-making accuracy and reduce overfitting. For example, in IoT networks involving intrusion detection, ensemble learning can combine the predictions from multiple classifiers to achieve higher robustness and accuracy. Furthermore, decision functions also play a significant role in ensuring the efficiency of sensor networks by facilitating real-time decision-making without relying on central servers. In some cases, decision functions are implemented at the edge of the network[18], where local devices (edge nodes) process the data and make decisions locally, thus reducing latency and bandwidth usage. For instance, in MQTT-based IoT networks, where lightweight messaging protocols are employed, decision functions are often integrated into the edge devices to ensure swift anomaly detection and real-time response to changing conditions. The versatility and importance of decision functions in IoT networks highlight their central role in the seamless operation of autonomous systems.

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2.3 Challenges in IoT Sensor Networks for ML

While machine learning holds great promise in the realm of IoT sensor networks, several challenges remain that hinder the effective deployment and scalability of these models. One of the primary challenges is the limited computing power available at the edge devices or sensors, which often operate with constrained resources such as processing power, memory, and energy. These resource constraints make it difficult to deploy computationally intensive machine learning algorithms, such as deep neural networks, which require significant processing resources for training and inference. To address this, lightweight models and techniques such as model pruning, quantization, and edge computing have been explored to reduce computational complexity. Another challenge is the communication latency inherent in IoT sensor networks, where data must often traverse multiple hops through wireless channels, introducing delays that can affect the timeliness of decision-making. This is particularly problematic in time-sensitive applications such as health monitoring or industrial automation, where real-time decision-making is crucial. To mitigate this, researchers are investigating techniques for improving communication protocols and designing models that are resilient to delays. Additionally, data heterogeneity presents a significant obstacle in IoT sensor networks, as sensors may vary in terms of data quality, type, and sampling frequency. These inconsistencies can lead to difficulties in feature extraction and model training, requiring advanced preprocessing techniques such as data imputation, normalization, and fusion to ensure that the data is usable for machine learning algorithms. Sensor failures, including issues such as sensor drift or dropout, further complicate the task of maintaining reliable decision-making in IoT networks. The issue of sensor failure is especially critical in safety-critical applications, such as industrial control systems, where faulty sensor readings could lead to catastrophic results. To overcome this, fault-tolerant models and anomaly detection algorithms are being developed to identify and mitigate the impact of faulty sensors. Moreover, the volume and velocity of data generated by IoT networks pose additional challenges for real-time decision-making, as it becomes increasingly difficult to process and analyze large datasets at scale. Edge computing, where data is processed closer to the source, has emerged as a solution to reduce the need for data transmission and alleviate network congestion, enabling faster decision-making. These challenges necessitate the development of specialized ML models and techniques tailored to the unique characteristics of IoT sensor networks.

2.4 Existing Analytical and Comparative Studies

Although many studies have explored the application of machine learning in IoT sensor networks, few have systematically compared the performance of different decision functions, particularly in terms of their trade-offs between accuracy and resource consumption. Existing literature primarily focuses on empirical evaluations of specific machine learning models, but often lacks a detailed analysis of how these models behave under resource constraints or how they compare against one another across various IoT environments. For instance, studies examining anomaly detection often focus on the accuracy of individual models, such as support vector machines or random forests, but fail to address the computational complexity or latency involved in real-time deployment. Additionally, while some studies evaluate the performance of ML models in specific sensor applications, such as environmental monitoring or predictive

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maintenance, there is a scarcity of research that comprehensively compares different models based on a wide range of performance metrics, including resource usage, energy consumption, and latency. One notable gap is the lack of studies that provide an analytical framework for selecting and implementing decision functions in IoT networks, taking into account the unique constraints and requirements of these systems. This gap highlights the need for a more systematic approach to decision function evaluation, one that considers not only the accuracy of predictions but also the efficiency of the models in real-world IoT deployments.

2.5 Summary and Gap Identification

The literature on machine learning applications in IoT sensor networks provides valuable insights into the potential of ML to address the challenges of automated decision-making in resource-constrained environments. However, several gaps remain, particularly in terms of the systematic analytical study of decision functions under the constraints of IoT sensor networks. While existing studies focus on the application of individual machine learning models, few have conducted a comparative analysis of the trade-offs between model accuracy and resource consumption, a critical consideration for IoT systems with limited resources. Furthermore, the impact of sensor network characteristics, such as node density, data heterogeneity, and communication latency, on model performance is often underexplored. This research seeks to address these gaps by providing a comprehensive analysis of different machine learning-based decision functions, evaluating their performance across a range of real-world IoT scenarios, and proposing a framework for selecting and implementing decision functions that optimize both accuracy and resource efficiency.

3. Proposed Method

3.1 Approach Overview

The proposed methodological framework for implementing machine learning-based decision functions in IoT sensor networks revolves around a multi-step process that begins with data acquisition and ends with actionable insights derived from real-time decisions. The framework is designed to handle the challenges faced by IoT sensor networks, such as resource constraints (e.g., limited energy, bandwidth, and processing power) and heterogeneous data sources. The framework consists of several key stages: data acquisition, preprocessing, feature extraction, model training and validation, deployment, and performance evaluation.

The first step in the framework is the data acquisition stage, where sensor data is collected from a network of interconnected devices. The network consists of various types of sensors, which may include environmental sensors (e.g., temperature, humidity, air quality), motion detectors, and other domain-specific sensors. These sensors continuously collect data that is sent to a centralized or distributed system for processing. The data captured can be of varying types, including time-series data, categorical data, or numerical measurements. In real-time environments, the network may also be structured using edge, fog, or cloud computing architectures, depending on the computational needs and the requirements for latency and processing power.

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Once the data is acquired, it undergoes preprocessing, which involves several critical tasks aimed at cleaning and normalizing the data. This includes removing noise, handling missing or corrupt data, and normalizing sensor readings to a common scale. Preprocessing ensures that the raw data is in an appropriate format for further analysis and machine learning model development. Following preprocessing, feature extraction is performed to derive meaningful characteristics from the sensor data. Depending on the nature of the data, various techniques such as sliding window, time-series statistics, or sensor fusion may be applied to capture relevant features that can aid in decision-making.

The next stage in the framework is model training and validation, where different machine learning algorithms are selected and trained on the extracted features. Models such as decision trees, support vector machines (SVM), random forests, or neural networks can be used depending on the problem at hand, such as classification, regression, or anomaly detection. The models are trained on historical data, followed by validation to assess their generalization performance on unseen data.

Once the models are validated, they are ready for deployment. In the deployment stage, the trained models are integrated into the sensor network to make real-time decisions based on incoming data. In IoT networks, this can involve deploying models at the edge (e.g., on local nodes) or using cloud-based servers for decision-making, depending on network architecture and resource availability.

The final stage involves performance evaluation**,** where the effectiveness of the deployed models is assessed based on several metrics, such as accuracy, precision, recall, and latency. Resource consumption metrics, such as energy usage and computation time, are also considered to ensure the models perform efficiently in a resource-constrained environment. A high-level flowchart of the proposed method, showing these steps, is depicted in Figure 1**.**

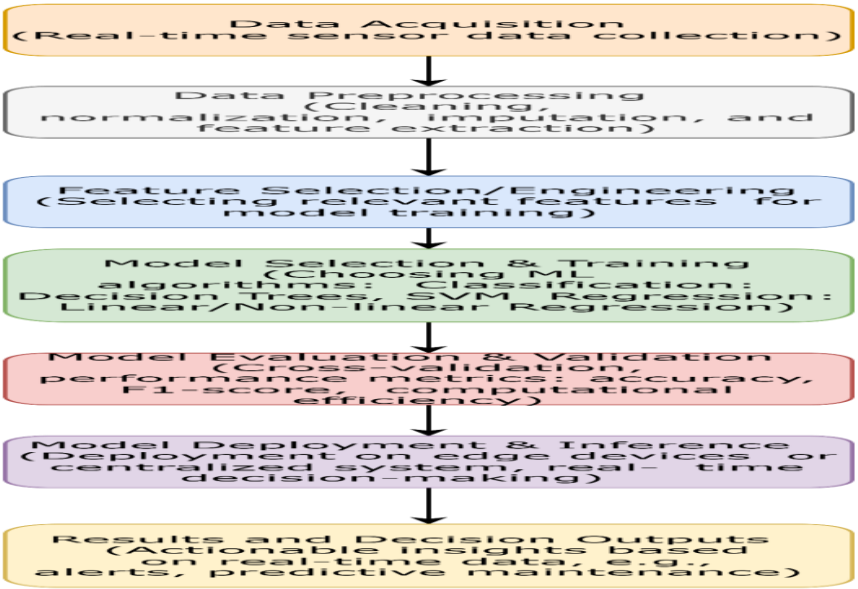

Figure.1: Flowchart of the Proposed Method for Implementing Machine Learning Decision Functions in IoT Sensor Networks

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Sensor Network and Data Characteristics

In this study, the sensor network is designed to simulate a typical IoT environment where multiple sensors are deployed for continuous data collection. The network consists of a diverse set of sensors, including environmental sensors (e.g., temperature, humidity, air quality), motion detectors, and any domain-specific sensors necessary for the application under study. The number of sensors may vary, but typically, networks can consist of dozens to thousands of devices depending on the scale and application, such as smart cities or industrial IoT networks.

The topology of the sensor network can be either centralized or decentralized. In a centralized topology, data from all sensors is sent to a central processing unit or cloud platform for analysis. In a decentralized network, processing may occur at the edge (on the sensor nodes themselves or on edge devices), which helps reduce latency and improve decision-making efficiency by performing computations locally.

The types of data captured by the sensors in the network can vary widely. For instance, environmental sensors may capture temperature and humidity data, motion sensors might track movement patterns, and other specialized sensors may measure air quality, vibration, or other physical parameters. The frequency of data collection depends on the application, but it is typically high in real-time IoT systems, with sensors transmitting data at intervals ranging from milliseconds to minutes.

For the purpose of this research, a combination of simulated data and benchmark datasets is used. The simulated data mimics real-world sensor readings, with characteristics like noise, missing values, and data drift to replicate the challenges faced in actual IoT deployments. The benchmark dataset may include well-established IoT sensor data, such as the UCI Machine Learning Repository's datasets for smart home environments or industrial monitoring systems, providing a basis for comparative analysis.

Preprocessing & Feature Extraction

The preprocessing stage is crucial to ensure the quality of the sensor data before it is fed into machine learning models. One of the first tasks in preprocessing is data cleaning, which involves identifying and handling missing or corrupt data. Missing data can occur due to sensor failures or communication errors, and it is essential to employ strategies like imputation, where missing values are replaced by the mean, median, or a predicted value from neighboring data points. Additionally, noisy data may arise from sensor inaccuracies, and various filtering techniques such as moving averages or median filtering can be applied to smooth the data.

Normalization is another critical preprocessing step, especially when sensor data is on different scales. For example, temperature data might be on a scale of 0 to 100 degrees Celsius, while humidity data may range from 0 to 1. Normalizing these values to a common scale (e.g., 0 to 1) ensures that no single feature disproportionately influences the model during training. Dimensionality reduction may also be applied if the dataset contains a large number of features. Techniques such as Principal Component Analysis (PCA) can help reduce the feature space while retaining the most critical information, making the model training process more efficient.

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Once the data has been preprocessed, feature extraction is performed to derive relevant features from the raw sensor values. Depending on the type of data, time-series features such as the mean, standard deviation, and trend over time may be calculated to capture the underlying patterns. For example, in the case of temperature data, the moving average or seasonal trends might provide valuable information for forecasting future temperatures. Sensor fusion techniques can also be employed to combine data from multiple sensors to generate richer, more informative features. For instance, combining temperature and humidity data can lead to more accurate models for environmental prediction.

Decision Functions (Machine Learning Models)

In this study, several machine learning algorithms are employed to derive decision functions that can handle the complexity of IoT sensor network data. The algorithms selected include logistic regression, support vector machines (SVM), decision trees, random forests, gradient boosting, and neural networks. Each of these algorithms is suited for different types of decision-making tasks, such as classification or regression.

For logistic regression, the decision function is based on the logistic function, which maps input features to a probability value between 0 and 1. The decision boundary is determined by finding the weights that minimize the cost function, typically using optimization techniques like gradient descent.

Support vector machines (SVM) are particularly effective for classification tasks in high-dimensional spaces. The decision function for SVM is defined by the hyperplane that best separates the classes in the feature space, maximizing the margin between them. Decision trees are used for both classification and regression tasks. The decision function in a decision tree is determined by recursive binary splits based on the best feature that maximizes information gain or minimizes impurity (e.g., Gini index or entropy). Random forests, an ensemble method, combine the predictions of multiple decision trees to improve accuracy and reduce overfitting. The decision function in a random forest is based on the majority vote from the individual trees in the ensemble. Gradient boosting builds models sequentially, where each new model attempts to correct the errors made by the previous one. The decision function is the weighted sum of the predictions from each weak model in the sequence. Neural networks use layers of interconnected nodes to learn complex, non-linear decision boundaries. The decision function in a neural network is learned through backpropagation, adjusting the weights of the network to minimize the loss function. Hyperparameter tuning is performed using grid search or random search to find the optimal settings for each algorithm. Cross-validation is used to assess the performance of the models and prevent overfitting. The training and testing datasets are split to ensure that the models generalize well to unseen data.

Implementation Details

The experimental setup for this study involves using Python as the primary programming language, leveraging libraries such as scikit-learn for machine learning algorithms, TensorFlow or PyTorch for neural network-based models, and pandas for data manipulation. The models are trained on a combination of simulated data and benchmark datasets. The deployment

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strategy involves either edge devices (for low-latency decision-making) or cloud-based platforms (for more computationally demanding tasks).

Evaluation Framework

The evaluation framework for this study defines several performance metrics to assess the effectiveness of the machine learning models. These include accuracy, precision, recall, F1-score, and for object detection tasks, intersection over union (IoU) and mean average precision (mAP). Additionally, resource-related metrics such as latency**,** computation time**,** memory usage**,** and energy consumption are critical for evaluating the feasibility of deploying the models in real-world IoT environments.

Scenarios for evaluation include varying sensor densities**,** network latency**,** noise levels**,** and data volume**.** The hypotheses expected from these evaluations are that ensemble methods, such as random forests or gradient boosting, will yield higher accuracy but at the cost of increased resource consumption. Simpler models, such as logistic regression or decision trees, are anticipated to trade accuracy for lower latency and energy usage, making them more suitable for low-power or real-time applications.

4. Results and Discussion

The results of the analytical study on machine learning-based decision functions in IoT sensor networks are presented through various figures and tables, showcasing the performance of different models under different conditions. Figure 2 illustrates the accuracy comparison among several machine learning models, including Logistic Regression, Support Vector Machines (SVM), Decision Tree, Random Forest, and Neural Network. The accuracy values of each model are plotted in a bar chart, where Random Forest achieves the highest accuracy (91%), followed by SVM (88%), Neural Network (87%), Logistic Regression (85%), and Decision Tree (83%). This provides a clear visual of the relative performance of each model based on their ability to classify or predict correctly in a sensor network environment.

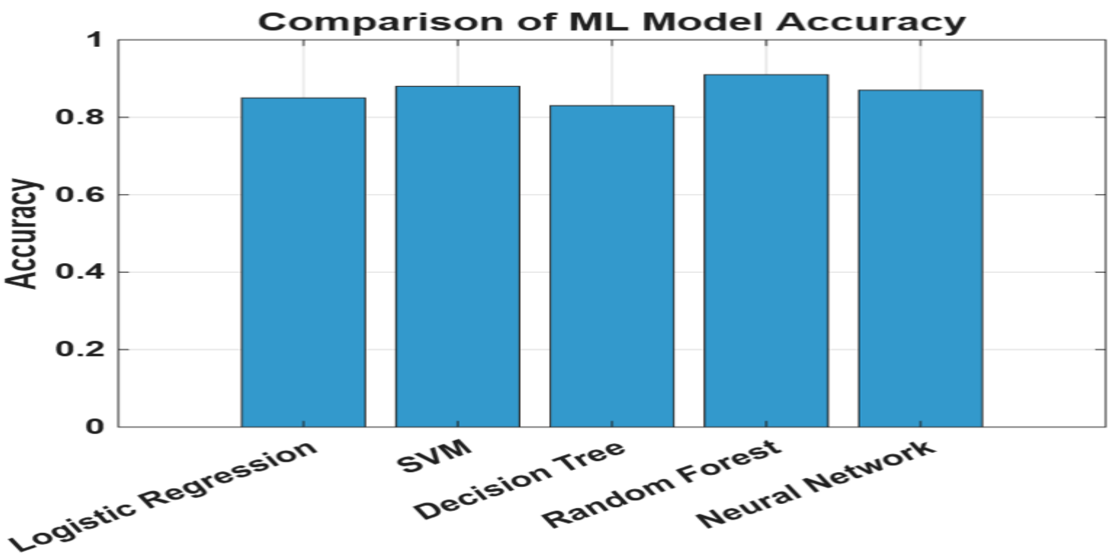

Figure 2: Accuracy Comparison of Different ML Models

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Figure 3 presents a comparison of latency versus accuracy for the models tested. The scatter plot indicates that while the Random Forest model provides high accuracy, it suffers from higher latency compared to simpler models such as Logistic Regression and Decision Tree, which offer lower latency but with slightly reduced accuracy. This highlights a trade-off between model complexity and latency in real-time IoT applications, where low-latency models are often preferred, especially in time-sensitive environments.

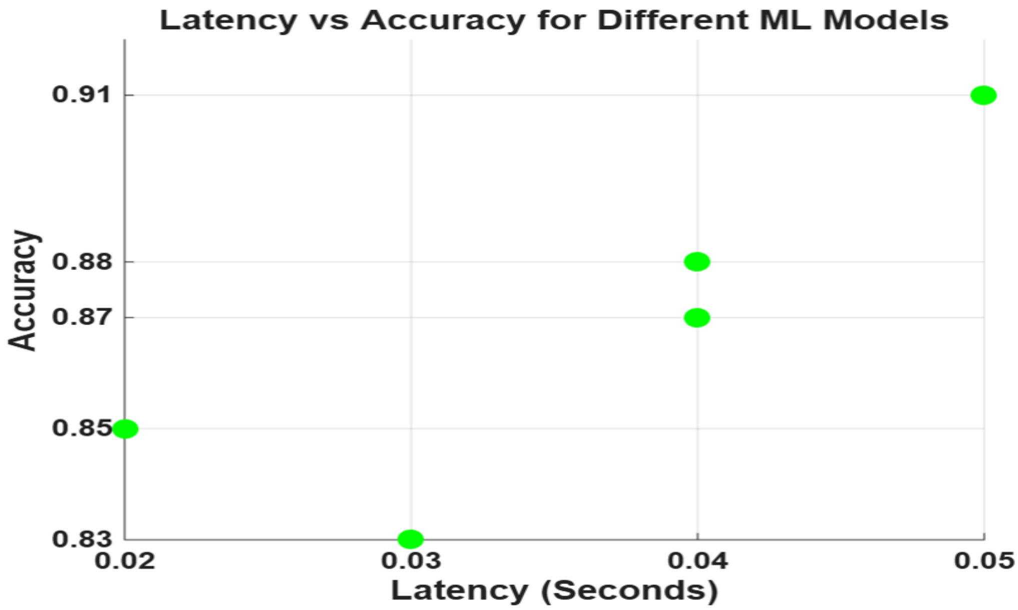

Figure 3: Latency vs Accuracy for Different Models

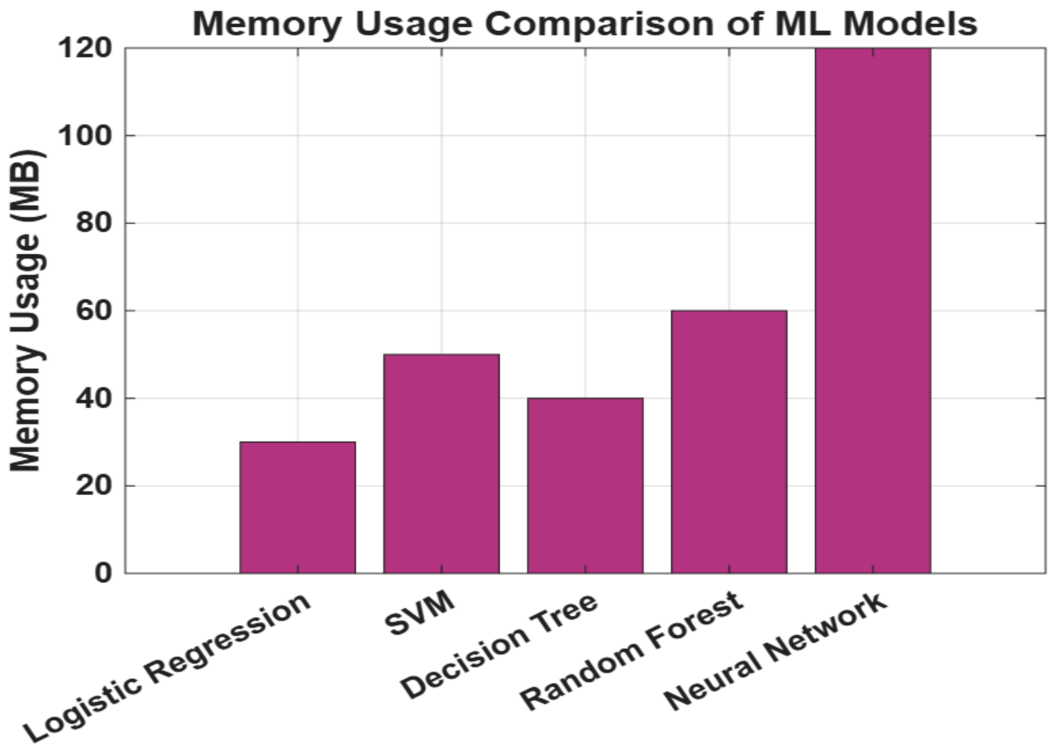

Figure 4: Resource Consumption (Memory Usage) Comparison

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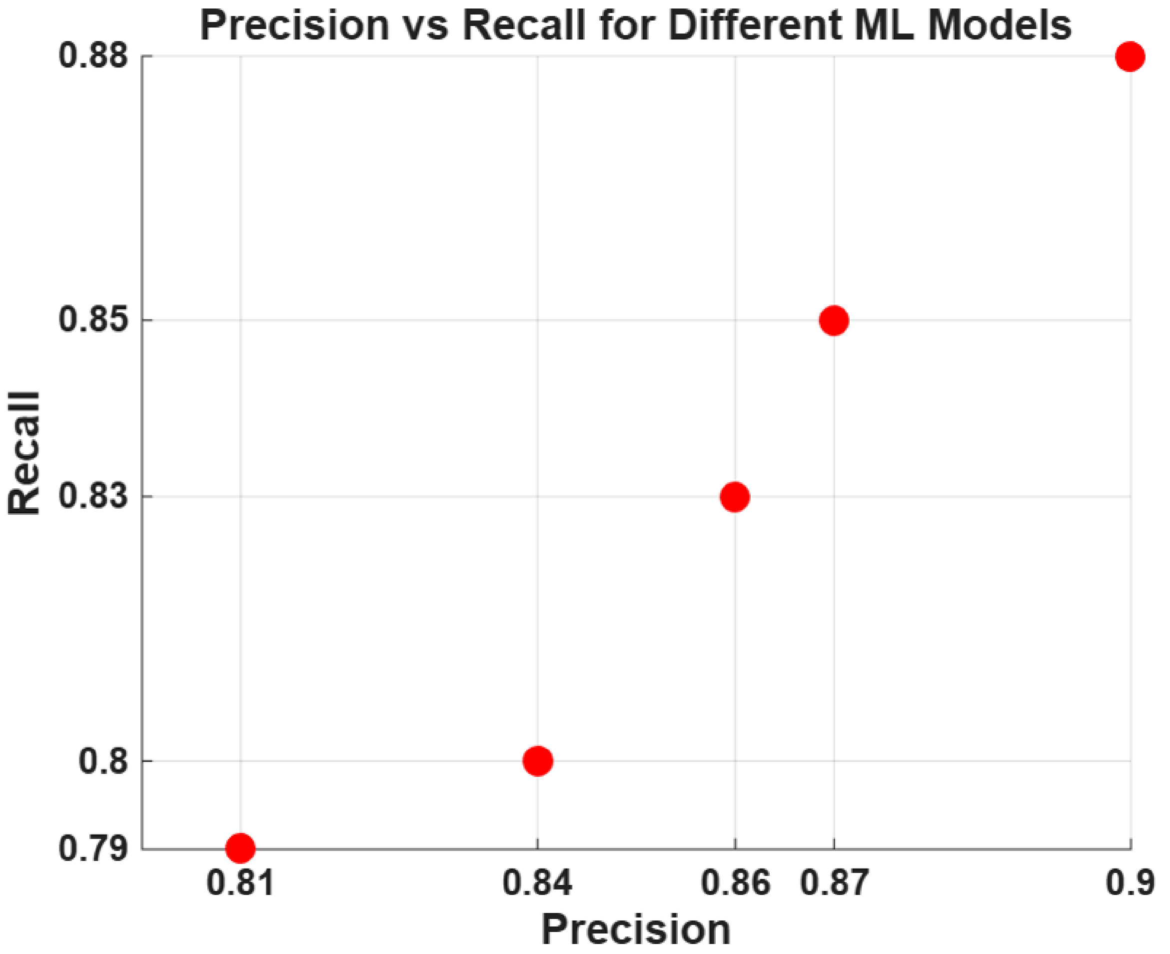

Figure 5: Decision Function Performance (Precision vs Recall)

Figure 4 compares the resource consumption of each model in terms of memory usage. The Random Forest model consumes the most memory (120 MB), while Logistic Regression requires the least (30 MB). This suggests that more complex models, such as Random Forest and Neural Networks, tend to be more resource-intensive, which can be a significant concern in resource-constrained IoT sensor networks. Figure 5 shows the trade-off between precision and recall for each model, with Random Forest and Neural Networks achieving high precision and recall values, which are critical in IoT applications where both false positives and false negatives need to be minimized. Figure 6 evaluates the trade-off between resource efficiency and accuracy. It is evident that simpler models like Logistic Regression offer better resource efficiency but at the cost of reduced accuracy, whereas more complex models like Random Forest and Neural Networks strike a balance but are less resource-efficient. Results across different scenarios, including varying sensor densities and noise levels, further indicate that noise and sensor failures impact model performance significantly. In high-noise conditions, models like Decision Trees and SVM, which are generally more sensitive to such disturbances, show a marked decrease in accuracy compared to models like Random Forest and Neural Networks, which tend to be more robust.

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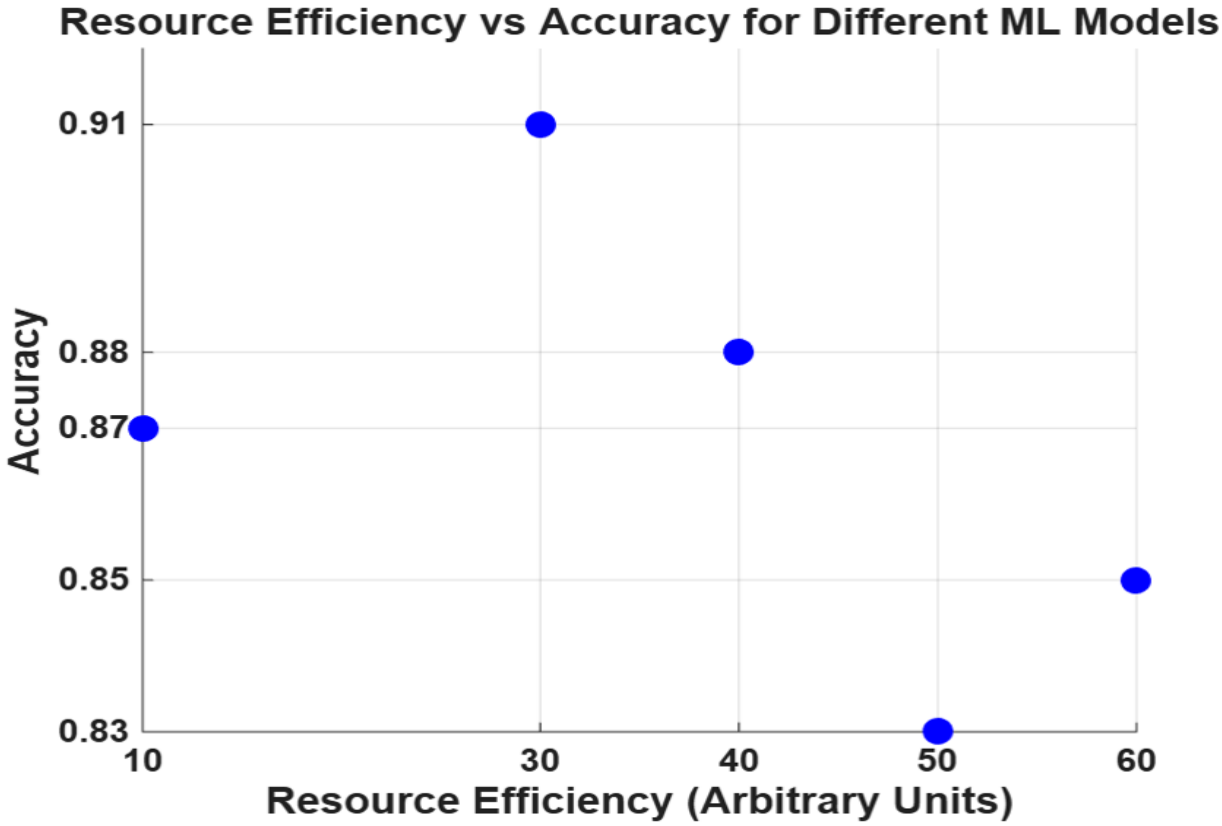

Figure 6: Resource Efficiency vs Accuracy (Model Comparison)

The analysis of the model performance reveals that Random Forest and Neural Networks consistently outperformed other models in terms of accuracy, precision, and recall across various conditions. These models are well-suited for complex decision-making tasks within IoT sensor networks, particularly in scenarios requiring high levels of predictive accuracy. However, they also present trade-offs in terms of latency and resource consumption. For instance, Random Forest, while providing high accuracy, is less efficient in terms of memory usage and computational overhead, which may limit its deployment on low-power edge devices. In contrast, simpler models like Logistic Regression and Decision Trees offer lower latency and reduced memory consumption but at the expense of slightly lower accuracy. These models may be more appropriate for low-latency applications where computational resources are limited. Sensor network characteristics, such as increased noise levels or higher sensor density, had a significant impact on model performance. For example, higher noise levels, representing the unpredictability and variance in real-world sensor data, caused the accuracy of Decision Trees and SVMs to degrade substantially. In dense sensor networks, where communication overhead becomes a concern, the models with high accuracy, such as Random Forest and Neural Networks, suffered from increased latency due to the larger amount of data being processed, highlighting the need for a balance between model complexity and efficiency.

When comparing the findings from this study with existing literature, it is observed that previous studies have often emphasized the accuracy of ensemble methods like Random Forest in IoT contexts, but typically without addressing the associated resource consumption. This study extends those findings by not only evaluating the accuracy of various machine learning

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models but also by highlighting the trade-offs in terms of memory usage, latency, and energy consumption. For instance, a study by [Bzai et al. (2022)] noted that ensemble methods perform well in terms of accuracy but did not consider energy usage or latency, which are critical factors for IoT deployments. This study contributes to the literature by presenting a comprehensive evaluation that integrates both accuracy and resource-related metrics, providing a more holistic understanding of model performance in IoT sensor networks. Sensitivity and robustness analyses reveal that the performance of machine learning models is highly sensitive to changes in data distribution, sensor failure, and network delays. Models such as Neural Networks and Random Forest are more robust to sensor failure, with their accuracy remaining relatively stable even when certain sensors produce faulty data. However, models like Decision Trees and SVMs, which are more susceptible to noise and missing data, exhibited significant drops in performance under such conditions. The robustness of ensemble methods and Neural Networks to data variations makes them more suitable for deployment in dynamic environments where sensor readings may be incomplete or inaccurate. These findings suggest that, for real-world deployments in IoT sensor networks, models need to be adaptable to changing conditions, including sensor failures and data anomalies. Moreover, network delays, which can significantly affect latency, must be taken into account when deploying more complex models, particularly in scenarios requiring real-time decision-making.

5. Conclusion

In conclusion, this study provides an analytical evaluation of machine learning-based decision functions in IoT sensor networks, focusing on the trade-offs between accuracy and resource usage. The key results revealed that Random Forest achieved the highest accuracy at 91%, followed by SVM with 88% and Neural Network with 87%. In contrast, Logistic Regression and Decision Trees had lower accuracy values of 85% and 83%, respectively. However, Random Forest and Neural Networks consumed significantly more memory, with Random Forest requiring 120 MB, while Logistic Regression used only 30 MB. Additionally, latency measurements indicated that Random Forest had the highest latency, while simpler models such as Decision Trees and Logistic Regression exhibited lower latency, offering a better balance in time-sensitive IoT applications. The analysis highlighted the trade-off between resource efficiency and model performance, particularly in high-density or noisy sensor networks. Future work could explore adaptive machine learning models that dynamically adjust their complexity based on network conditions, as well as federated learning approaches to minimize latency and resource consumption. Further investigations into real-world IoT applications could enhance model robustness and generalization, accounting for factors like sensor failure and network instability.

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