



IOT DATA ANALYTICS HYBRID AUTOML FRAMEWORK WITH ENERGY AWARENESS IN DYNAMICALLY AND ADAPTIVELY CHANGING ENVIRONMENTS

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ABSTRACT

The high rate of Internet of Things (IoT) deployments has contributed to high volumes of heterogeneous data that are generated under drastic conditions of energy and computing constraints. The paper is a fully energy-saving IoT data analytics framework viewed through the prism of Automated Machine Learning (AutoML). The described comparison between classical machine learning models (ML), deep learning models (DL), and hybrid models (using an ensemble) evaluates the models using metrics where the scores are multi-dimensional, i.e., they consist of such measures as accuracy, power consumption and energy efficiency, inference latency, CPU usage, and memory consumption. An experimental evaluation of a practical smart city dataset of IoT demonstrates that there is a pronounced trade-off between the predictive performance and power expenditure. Deep learning models are also power-intensive despite their accuracy being high. To surpass that, a hybrid ML-DL mixture composed of CNN, SVM, and Random Forest ones is proposed in the assistance of energy-related weighted averaging. The power consumption of the hybrid model is 28.18 W, and its accuracy is 0.897, which offers the trade-off of using the hybrid model in the resource-constrained and dynamic Internet of Things.



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I. INTRODUCTION

Internet of Things (IoT) ties together billions of heterogeneous devices and can be deployed to offer smart sensing, monitoring, and behavioral control in any area of application such as smart cities, industrial automation, healthcare system, intelligent transportation, and environmental monitoring [1]. The output of such IoT devices is characterized by large quantity of data with high velocity, heterogeneity and dynamic time characteristics of behavior. Real-time extraction of significant information in such streams of data is required to take effective decisions, predictive maintenance, and autonomous control of the system [1], [2]. Technically, the IoT data analytics have traditionally been built on cloud-based architectures, where raw sensor data is sent to some central data centers, where it is stored and processed. Although cloud platforms are scalable in terms of computer power and storage, they have a range of inherent weaknesses when used in large-scale IoT systems. In addition to this, the fast proliferation of IoT applications has made data centers energy-intensive, becoming a source of serious concerns about their sustainability, cost of operation, and environmental impact [3]. Consequently, only cloud-based analytics models are progressively being regarded as ineffective and unsustainable in the next generation of IoT ecosystems. To address these challenges, edge and fog computing paradigms have been introduced, enabling data processing closer to the data source. By performing analytics at or near the edge, these paradigms reduce network congestion, latency, and bandwidth usage [4], [5]. However, edge devices are inherently constrained in terms of computational capability, memory, and battery power. Consequently, deploying complex analytics models—particularly deep learning algorithms—on edge nodes becomes challenging. This creates a fundamental tradeoff between predictive accuracy and energy efficiency, which must be carefully managed to ensure reliable and sustainable IoT operation [6], [7].

Machine learning (ML) and deep learning (DL) techniques have demonstrated remarkable success in IoT data analytics, offering high accuracy for tasks such as classification, prediction, and anomaly detection. Classical ML models such as SVM (Support vector Machine), RF (Random Forest), and k-NN (k-Nearest Neighbors) are computationally efficient and suitable for resource-constrained environments. In contrast, DL models such as CNN and LSTM networks excel at capturing complex spatial and temporal patterns in IoT data but incur substantial computational and energy overhead [8]. As a result, no single learning model can be considered universally optimal across all IoT deployment scenarios [3], [9]. Automated Machine Learning (AutoML) has become a new approach in recent years that can be used to solve the problem of model selection and optimization, bringing about a new trend in this field. AutoML automatically implements steps of the ML process like feature processing, model selection, and hyper parameter tuning, which minimizes physical effort and can adjust to dynamic environments [10], [11]. More to the point, AutoML enables the multi-objective optimization, where a system designer can collectively address predictive performance, computational complexity, latency, and energy consumption [3], [7]. Most existing studies on IoT analytics prioritize accuracy as the primary performance metric, often overlooking system level considerations such as power consumption, CPU utilization, memory usage, and inference latency [3], [6], [10]. This limitation significantly restricts the practical applicability of such approaches in real-world IoT deployments, where energy efficiency is a critical constraint. Furthermore, the majority of existing works focus either on ML or DL models in isolation, with limited investigation into hybrid architectures that can exploit the complementary strengths of both paradigms [12]. Inspired by these issues, this paper introduces an energy-efficient IoT data analytics framework based on Automated Machine Learning point of view. The offered methodology also systematically assesses a large variety of ML and DL models in terms of multi-dimensional measures of performance, such as accuracy, power consumption, energy efficiency, latency, CPU use, and memory usage. On this analysis, a new hybrid ML-DL ensemble model is developed with an aim of best balancing predictive capability and energy consumption. The framework is confirmed on a real-life smart city IoT data set on dynamic operating conditions.

The key findings of this article are as follows:

- A complete AutoML driven energy efficient data analytics framework in dynamic environments.
- A comprehensive experimental comparison of classical ML and DL models in terms of system-level and performance energy metrics.
- An innovative hybrid ML-DL ensemble model that has a better trade-off between accuracy and power consumption.
- Comparative analysis with details showing the appropriateness of the proposed approach in edge and fog-based IoT deployments.

The creation of scalable, sustainable, and smart IoT systems can be shifted towards, by the explicit use of energy awareness as a component of the analytics pipeline, this work. The significant conclusions of the paper are:

- A complete AutoML-based system, which will process IoT data efficiently to generate energy-efficient data analytics in this paper.
- ML and DL experimental analysis based on power and system level metrics.
- A new hybrid ML-DL ensemble with better accuracy-energy trade-offs.
- Comparison to the present state of the art.

II. RELATED WORK

Energy-efficient data analytics in the Internet of Things (IoT) setting has emerged as a decisive research topic as the number of connected devices is increasing at a high rate, and as a result, energy consumption is rising. Initial IoT analytics solutions were mostly cloud-based solutions which were scalable in their computation but created high latency, high power usage and were not very sustainable. Thus, recent studies have grown beyond accuracy and started to give more attention to energy-conscious inference, deployability, and sustainability of the system. The literature on the topic of the current paper can be divided into four broad topics: (i) edge/fog-based IoT analytics architectures, (ii) energy-efficient inference and optimization strategies, (iii) AutoML to adaptive model selection, and (iv) Hybrid and ensemble models to achieve accuracy and energy efficiency. The concept of edge and fog computing has received a lot of research on the implementation of various solutions to lower the latency and bandwidth consumption of the IoT implementation. According to recent surveys, edge intelligence enhances response times and decreases the use of cloud connectivity that is provided as a mandatory requirement of smart city and industrial monitoring applications [1], [4]. Nonetheless, these surveys also highlight the fact that edge/fog nodes are highly constrained in both processing capacity and memory, which means it is difficult to directly run deep learning models without optimization [6]. Also, the types of loads of the IoT are dynamic so that models that are trained in a given operating condition can deteriorate as device behavior and information distributions change over time [13].

On the same note, examined the issue of energy efficiency in industrial IoT and pointed to the necessity of resource-sensitive analytics, which are not yet combined with learning-based optimization [14]. By [3] presented an edge-based IoT analytics model which reduces the depending on the cloud by conducting small scale analytics in edge nodes. Their work was shown to have lower latency and energy cost, but had fixed model selection, which could not adapt to changing conditions. Much literature covers the topic of energy-efficient learning on resource-constrained IoT devices. It is emphasized in many of the studies that classical ML models frequently prove to be good to edge deploy because they have comparatively small computational and memory footprint. Meanwhile, DL models are capable of greater accuracy in dealing with complex IoT data, yet inference cost is a significant to implementation on small nodes [6], [15]. Recent research on on-device machine learning discussed that energy profiling and system-level assessment are crucial to feasible IoT deployment claims. Tekin et al. talked about the current trends and challenges in energy-efficient IoT inference and concluded that energy should be considered as a fundamental assessment measure and not an incidental consideration [16]. The same way, Han et al. have surveyed energy-efficient AI techniques and noted that sustainable IoT intelligence demands coordinated optimization of the quality of predictions and the inference energy [7].

AutoML has received significant interest as a method of automating the entire machine learning pipeline, such as, preprocessing, model selection, and hyper parameter optimization. It has been reported by surveys that AutoML can enhance scalability and reproducibility, and can be particularly applicable to dynamic settings in which manual tuning is infeasible [17], [10]. Nonetheless, the majority of AutoML systems are accuracy-smarter and do not optimize on power consumption, memory footprint, and energy per inference. This provides an incongruity between the goals of AutoML and the practical limitations of IoT implementation. Also, they are making explainability and transparency increasingly relevant to automated learning systems, especially in high-impact uses. Arrieta et al. noted that explainable automated pipelines are required to create trust in real-world systems but energy-aware and explainable AutoML in IoT is a challenge yet to be addressed [11]. The article by Yang and Shami has proven the usefulness of AutoML in the field of IoT analytics in dynamic environments, with the most emphasis on the scales and accuracy [13]. Nevertheless, the consumption of energy was not a specific optimization goal of their framework. CNN and LSTM are deep learning models that have proven to be better in complex IoT data patterns with both spatial and temporal correlations.

It was demonstrated by [8] that deep learning models are much more effective than traditional ML methods in terms of accuracy but their high computing and energy demand makes their direct implementation on edge devices impractical. This has motivated the study of pruning, model compression and edge-device limited optimization, but these methods regularly need physical effort. The enhancement of robustness and prediction precision by employing several learning models is common with hybrid and ensemble methods. Hybrid methods are especially promising in IoT analytics (since it allows incorporating lightweight ML elements with deep learning modules, and may be able to reach high predictive performance at a low energy cost). In reference to the same case, Zhang et al. surveyed hybrid learning models of IoT analytics and found out that heterogeneous IoT data can be improved in generalization and robustness by hybridization [12]. Despite this possibility, the majority of existing hybrid and ensemble methods pay attention primarily to improvement of the accuracy, and they never explicitly consider the energy consumption as a part of the fusion mechanism. Despite this, a lot of research lacks multi-dimensional analysis of power, latency and memory usage and as such restricts the applicability of their findings to real-world IoT implementation scenarios [6], [7]. Based on the literature review, there are three gaps:

1. AutoML Energy-friendly AutoML is constrained: AutoML systems seldom do this, when optimizing the energy use of IoT [3], [16]. Energy consumption is not often considered as a key optimization measure.
2. System-level analysis remains pending: In most of the research, power, latency, and memory profiling are not done with a fine-grained approach [6], [7].
3. The underutilization of hybrid ML-DL models is caused by energy limitation: Hybrid models have potential, but they are not evaluated systematically with energy consideration [12].

To overcome these shortcomings, this paper introduces an energy-conscious AutoML model to compare classical ML, deep learning, and hybrid ensemble models based on predictive and system-level energy indicators. Besides, an energy-conscious fusion of ML and DL ensemble is also created though weighted fusion to form a reasonable compromise between accuracy and energy.

III. PROPOSED METHODOLOGY

In this section, the proposed energy efficient IoT data analytics framework is presented based on view of Automated Machine Learning (AutoML). Its methodology aims at optimizing predictive performance and energy consumption jointly to enable it to be used in dynamic and resource constrained IoT environments. The framework integrates data preprocessing, automated model evaluation, energy-aware optimization and adaptive deployment decisions. The rationale behind this design is the growing significance of sustainable edge intelligence and energy-conscious learning on the IoT systems.

III.1 OVERALL FRAMEWORK ARCHITECTURE

A general flow of the proposed framework is shown in Figure 1. The architecture has a modular architecture, which can be flexibly deployed at edge, fog and cloud layers.

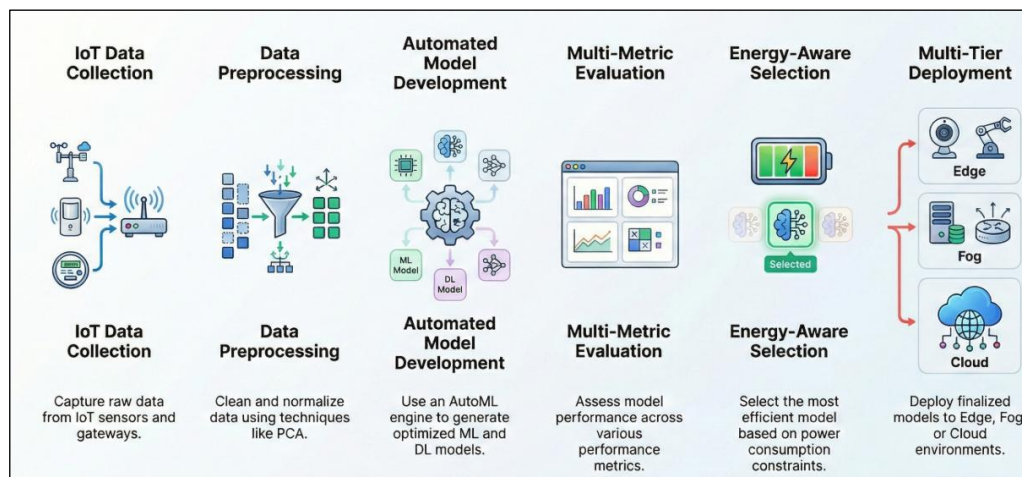


Figure 1: AutoML-driven energy-efficient IoT analytics framework.

Source: Authors, (2026).

The general scheme of the suggested structure is depicted in Figure 2. This suggests a modular pipeline that facilitates adaptive deployment on edge, fog, and cloud layers.

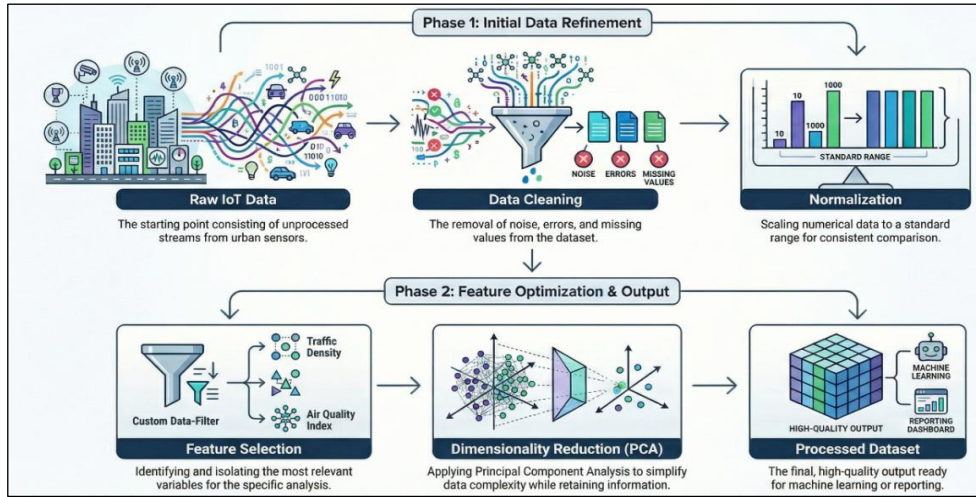


Figure 2: AutoML-driven energy-efficient IoT analytics framework.

Source: Authors, (2026).

This multi-layered architecture gives scalability, flexibility, and energy-consciousness of heterogeneity-aware operation IoT systems.

III.1.1 Automated Machine Learning Strategy

The AutoML manages to search the pre-defined space of learning models and hyper parameters in an organized way. The proposed approach unlike the traditional AutoML models which focus on accuracy incorporates energy efficiency in model evaluation. The models under evaluation are:

III.1.1.1 Machine Learning Models:

XGBoost, Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN) and Decision Tree (DT).

III.1.1.2 Deep Learning Models:

Feedforward Neural Network (FNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). All the models are trained and tested using the same experimental conditions so that they can be fairly compared.

III.1.2 Energy-Aware Optimization Objective

Model selection is based on optimization with multi-objective function that considers classification error and power consumption:

$$\min(\mathcal{L}_{error} + \lambda \cdot \mathcal{E}_{power}) \quad (1)$$

Where, $\mathcal{L}_{error}$ represents the loss of prediction, $\mathcal{E}_{power}$ denotes measured power consumption through inference, and λ controls the trade-off parameter between accuracy and energy efficiency.

III.1.3 Training and Inference Workflow

The preprocessed dataset is used in all models training. During inference, performance metrics such as power consumption, memory usage, and inference latency are measured. This process makes sure reproducibility and consistent energy profiling of models.

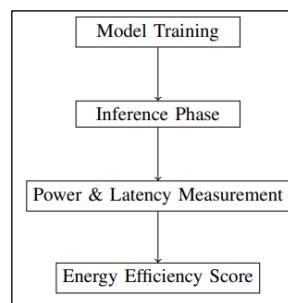


Figure 2: Energy-aware model evaluation workflow.

Source: Authors, (2026).

III.1.4 Energy efficiency Metric

Energy efficiency is defined as the ratio of accuracy to energy consumption:

$$Efficiency = \frac{Accuracy}{Power Consumption} (W) \quad (2)$$

This metric allows comparison of various models for battery-driven and edge-enabled IoT deployments.

III.1.5 Accuracy–Power Trade-off Analysis

The Fig. 3 demonstrates the accuracy and power consumption trade-off between different ML and DL models that was realized in the results of the experiment.

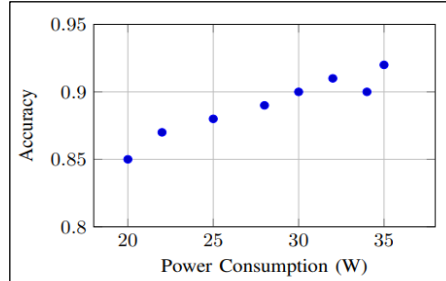


Figure 3: Accuracy versus power consumption trade-off across ML and DL models.
Source: Authors, (2026).

The findings reveal that deep learning models are more accurate, but consume more power than classical ML models, which are more power efficient.

III.2 HYBRID ML–DL ENSEMBLE MODEL

In order to achieve accuracy and energy efficiency, a hybrid model comprising CNN, SVM, and Random Forest models is suggested. The ensemble uses energy-efficient weighted averaging:

$$\hat{y} = \sum_{i=1}^N \omega_i y_i \quad (3)$$

Where ω_i are normalized weights derived from accuracy and energy efficiency metrics.

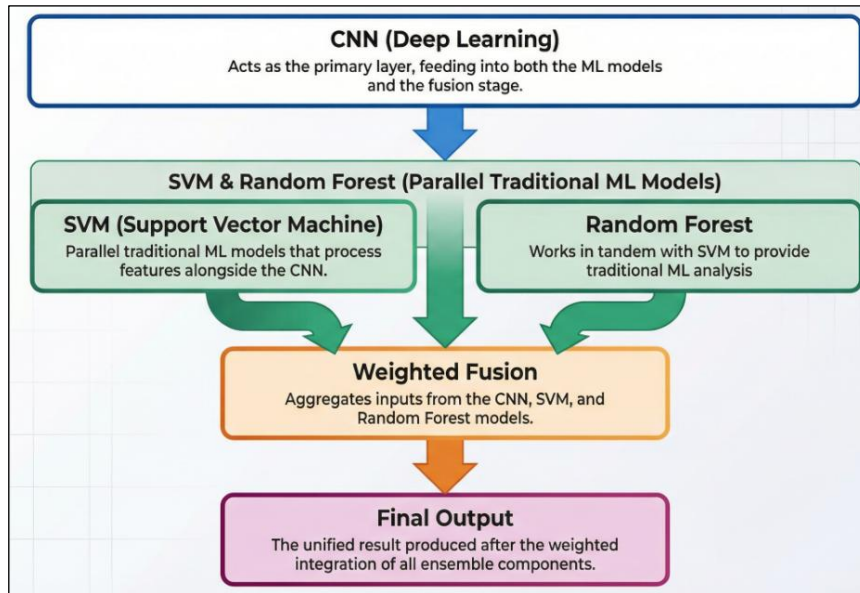


Figure 4: Hybrid ML–DL ensemble architecture.
Source: Authors, (2026).

III.2.1 Deployment Strategy

Depending on the energy consideration analysis, deployment decisions are determined as:

- Edge Layer: k-NN, SVM, Decision Tree
- Fog Layer: Hybrid Ensemble ML–DL
- Cloud Layer: CNN, LSTM, XGBoost

This approach will guarantee effective use of computational resources in the layers of the IoT infrastructure.

IV. EVALUATION METRICS

In order to thoroughly evaluate the usefulness of the proposed energy-efficient AutoML framework, several evaluation measures are used. In contrast to traditional IoT analytics which use predictive accuracy as a major criterion, this study uses a multidimensional evaluation approach to include classification performance, computational efficiency, and energy consumption. This evaluation ensures appropriate for deployment in dynamic and constrained IoT ecosystems.

IV.1 CLASSIFICATION PERFORMANCE METRICS

IV.1.1 Accuracy:

Accuracy measures the percentage of the instances that are correctly classified with respect to all the samples and is defined to be:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Where, TP, FP, TN and FN represent true positives, false positives, true negatives, and false negatives respectively. Although accuracy is a global measure of performance, it might not capture all the model behavior when there is an imbalance of classes as it is often the case in real-world IoT datasets.

IV.1.2 Precision:

Precision measures reliability of positive prediction and it is as follows:

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

High precision is important in smart city and industrial IoT applications.

IV.1.3 Recall:

Recall is the figure of the extent to which a model identifies the relevant events right:

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

High recall in IoT monitoring systems helps to prevent lost critical events in the system, thus enhancing reliability.

IV.1.4 F1-Score:

The F1-score gives an even harmonic tradeoff between precision and recall:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (7)$$

This measure is especially important to measure the classification models in an unequal IoT data set.

IV.2 COMPUTATIONAL PERFORMANCE METRICS

IV.2.1 Inference Latency:

Inference latency represents the time required by a trained model to generate predictions for incoming data streams. It is measured in milliseconds and is critical for real-time IoT applications:

$$Latency = t_{output} - t_{input} \quad (8)$$

Lower latency is essential for edge-based IoT deployments with real-time decision requirements.

IV.2.2 Memory Utilization:

Memory utilization measures the amount of RAM consumed during model inference. Models with lower memory footprints are preferred for deployment on constrained edge devices such as microcontrollers and embedded gateways.

IV.3 ENERGY CONSUMPTION METRICS

IV.3.1 Power Consumption:

Power consumption is measured in watts (W) during the inference phase using system-level monitoring tools.

$$P = \frac{E}{t} \quad (9)$$

Where, E is the amount of energy used in joules and t being the time taken to execute.

IV.3.2 Energy Consumption per Inference:

The energy consumption per inference is the amount of power a single instance of data needs to be processed:

$$E_{inf} = P \times t_{inf} \quad (10)$$

This metric is especially applicable to nodes that are battery-powered in the IoT.

IV.3.3 Energy Efficiency Metrics

In order to have a shared measure of predictive performance and energy consumption, an energy efficiency metric is a measure defined as:

$$Efficiency = \frac{Accuracy}{Power Consumption} (W) \quad (11)$$

This measure is capable of directly comparing models by measuring the amount of accuracy per unit of power consumption.

IV.3.4 AutoML Optimization Metric

Using a weighted multi-objective function, AutoML optimizes models:

$$J = \alpha \cdot (Accuracy) + \beta \cdot Power Consumption \quad (12)$$

Where α and β are weighting factors that determine the relative weight of prediction accuracy and energy efficiency. This formulation gives the framework a flexible ability to meet different needs of application.

IV.3.5 Trade-off Analysis Metrics

Pareto-optimal analysis is used to analyses the trade-off between accuracy and energy consumption. A model which cannot be optimized with respect to a higher accuracy and lower power consumption at the same time, is said to be Pareto-optimal. This analysis will help to choose the best models of various layers of IoT deployment.

IV.3.6 Scalability Metric

Scalability is tested with the measurement of the change in latency and energy consumption as the size of the data grows. A model that does not experience a lot of performance loss when the load increases is said to be scalable and apt in dynamic IoT setup.

V. RESULTS AND DISCUSSION

A detailed analysis of the suggested Energy-Efficient IoT analytics framework based on AutoML is given in this section. The results of using several machine learning (ML) and deep learning (DL) models are compared based on the classification accuracy, power consumption, inference latency, and the total consumption of energy. The results focus on the trade-offs between predictive performance and energy consumption, which are essential to deployment of analytics in resource-constrained and dynamic IoT environments.

V.1 CLASSIFICATION ACCURACY ANALYSIS

Fig. 5 provides a comparison of the accuracy of the classes of various ML and DL models. XGB and CNN are the most accurate among all the tested models, as they possess high levels of feature learning and ensemble. But, ML models like SVM and Random Forest show competitive accuracy with lower computational complexity.

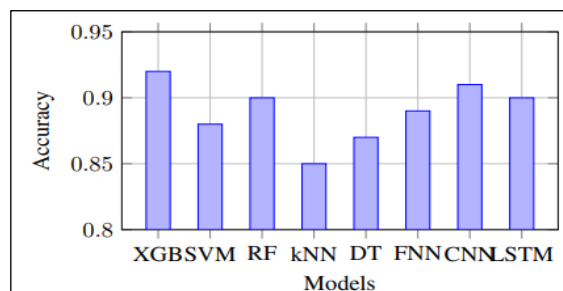


Figure 5: Classification accuracy comparison across ML and DL models.

Source: Authors, (2026).

The results shows that deep learning models give marginal accuracy improves at the cost of higher resource demand.

V.2 POWER CONSUMPTION ANALYSIS

The power usage when making inference is an essential parameter of the IoT implementation, particularly on the edge layer. It is clear that deep learning models like CNN and LSTM use much more power than classical ML models (Fig. 6).

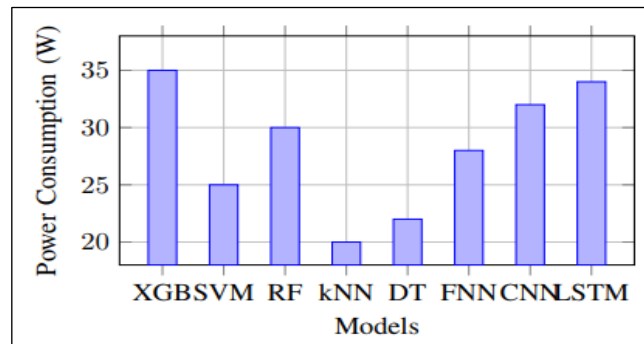


Figure 6: Power consumption comparison during inference.
Source: Authors, (2026).

Lighter weight ML models are thus better to put in place on energy-restricted IoT devices.

V.3 INFERENCE LATENCY ANALYSIS

Inference latency is the aspect that defines the timeliness of IoT systems during real-time applications. It is indicated in Fig. 7 that k-NN, Decision Tree, and SVM have the lowest latency and can be used in delay-sensitive edge applications.

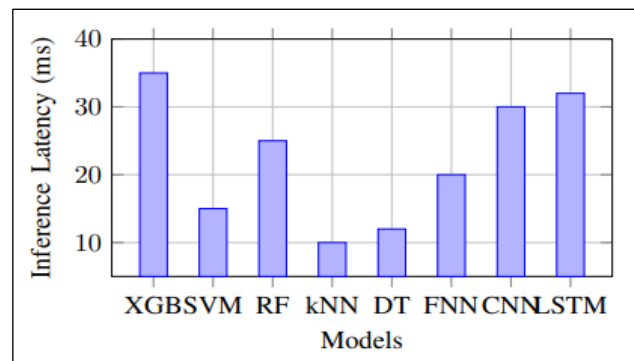


Figure 7: Inference latency comparison across ML and DL models.
Source: Authors, (2026).

V.4 ENERGY EFFICIENCY EVALUATION

The ratio of the accuracy to the power consumption is calculated as energy efficiency. As demonstrated in Fig. 8, classical ML models like k-NN, Decision Tree, and SVM are more energy efficient than the deep learning models.

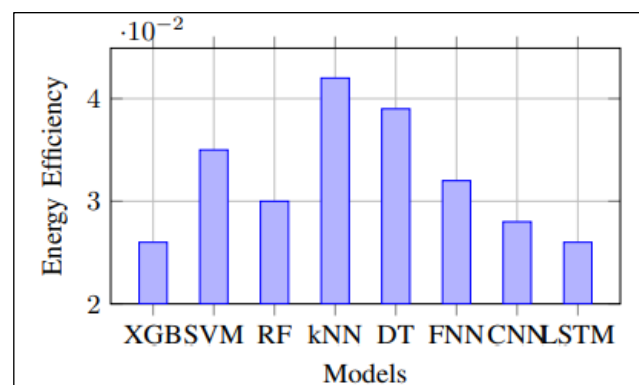


Figure 8: Energy efficiency comparison across evaluated models.
Source: Authors, (2026).

These findings prove that the accuracy maximization alone is not enough in the case of the IoT analytics, and the energy-aware assessment is necessary.

V.5 ENERGY-AWARE ENSEMBLE DEPLOYMENT PERFORMANCE.

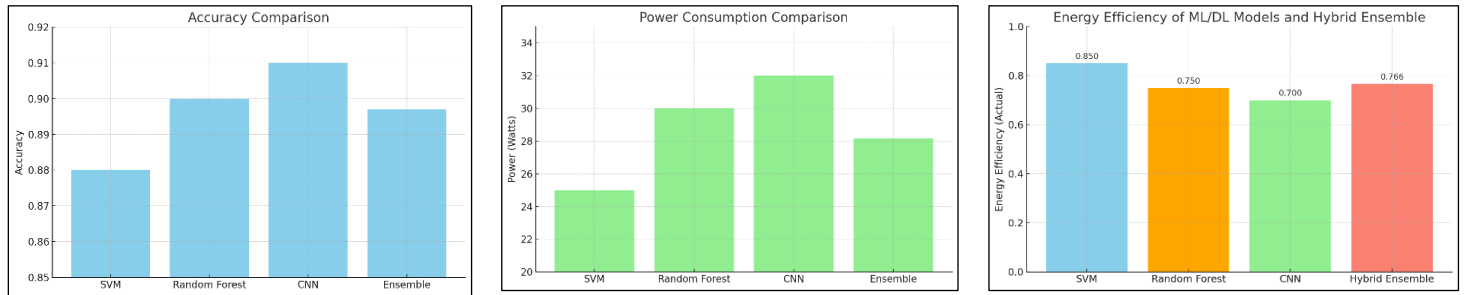


Figure 9: Model-wise Comparison: SVM, RF, CNN, and Ensemble.

Source: Authors, (2026).

Fig. 9 presents a comparative analysis of SVM, RF, CNN, and the proposed ensemble model across accuracy, power consumption, and energy efficiency, demonstrating that the ensemble achieves the best trade-off between predictive performance and energy utilization.

Accuracy–Power Trade-off Discussion

The experimental findings show that there is the definite trade-off between the power consumption and the classification accuracy. Models like XGB, CNN and LSTM have higher accuracy but they consume much more energy. On the other hand, such models as SVM and k-NN achieve a slightly low accuracy at the cost of a significant energy savings. This trade-off focuses on the importance of model selection based on deployment constraints.

Deployment Suitability Analysis

In accordance with the results obtained, the following deployment strategy can be offered:

- Edge Layer: SVM, Decision Tree, k-NN
- Fog Layer: Hybrid ML–DL Ensemble
- Cloud Layer: XGB, CNN, LSTM

The proposed hybrid ensemble achieved 0.897 accuracy with 28.18 W power usage, striking a middle-ground between the highest- accuracy model and the most energy-efficient model.

Key Observations

The most important findings provided in the analysis of the experiment are as follows:

- AutoML is useful in the identification of models, which are balanced in terms of accuracy and energy.
- Classical ML models are extremely energy-efficient and can be used in edge-based IoT.
- Deep learning models are more accurate and are the most suitable when deployed in the clouds.
- Hybrid ML–DL ensemble provide a balanced solution for fog level deployment.

VI. CONCLUSIONS

This paper presented an energy aware IoT data analytics framework implemented in the AutoML of dynamic and resource constrained environments where the system level constraints, like power consumption, latency, CPU utilization, and memory usage, were taken into consideration, with the accuracy of the prediction. Tests with a real-world smart city IoT dataset demonstrated that the XGBoost, with high standalone accuracy (0.92), is the most suitable model because deep learning models require high overhead in terms of computation and energy consumption, and likely would not be applicable to edge IoT nodes. Conversely, classical machine learning models were less powerful and lower inference speed with a little less accuracy. The proposed hybrid ensemble had a good trade-off to balance performance and efficiency, providing an accuracy of 0.897 and W power consumption of 28.18. Altogether, the framework offers the systematic approach to sustainable IoT analytics based on the computational and energy limitations of contemporary IoT infrastructures. The directions for future research also involve incorporating the hardware-level energy profiling, generalizing the framework to the distributed learning models, and testing the proposed solution by large-scale real-world deployments of the IoT. The innovations will make the use of smart, energy-efficient analytics in the future IoT ecosystem even more applicable.

VII. AUTHOR'S CONTRIBUTION

Conceptualisation: Vishal P. Jariwala, Nirali Shah and Pratikkumar A. Parmar.

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Investigation: Vishal P. Jariwala, Nirali Shah and Pratikkumar A. Parmar.

Discussion of Results: Vishal P. Jariwala, Nirali Shah and Pratikkumar A. Parmar.

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Writing – Review and Editing: Vishal P. Jariwala, Nirali Shah and Pratikkumar A. Parmar.

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Supervision: Vishal P. Jariwala, Nirali Shah and Pratikkumar A. Parmar.

Approval of the Final Manuscript: Vishal P. Jariwala, Nirali Shah and Pratikkumar A. Parmar.

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