

A Smart and Energy-Efficient Framework for Micro Electric IoT Applications Leveraging Deep Learning

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Article History:

Received: 07-01-2025

Revised: 05-02-2025

Accepted: 17-03-2025

Abstract:

This research introduces an innovative and energy-efficient framework that leverages advanced deep learning techniques, specifically Bayesian Neural Networks (BNN), and the Dragonfly Algorithm to optimize energy usage in micro electric IoT environments. The framework integrates BNNs, known for their probabilistic modeling capabilities, to enhance predictive analytics and decision-making processes. By infusing uncertainty estimates into the model predictions, the system achieves more informed and adaptive responses, thereby reducing unnecessary energy expenditures during periods of low activity. The Dragonfly Algorithm is employed for dynamic resource allocation, allowing devices to intelligently adapt to varying workloads in real-time. Through extensive experiments, we observe a notable reduction of 0.17 in mean-square error (MSE) and 0.8 reduction in MAE and 0.7 reduction in RMSE and 8.8 error reduction in MAPE.

Keywords: Internet of Things (IOT), Deep learning, Dragonfly algorithm, Bayesian Neural Network

1. Introduction

The management of energy in smart grids through automated techniques for future load forecasting is an intriguing field of research. Smart grids provide a dependable and secure infrastructure for the distribution of electrical energy to a diverse range of consumers [1]. The amount of energy produced is directly affected by how much consumers use [2]. Many consumers lack expertise in managing their energy demands, which leads to unnecessary financial costs and wasted energy. Likewise,

energy producers aim to lower costs and optimize power generation, making efficient scheduling and management essential [3].

Energy forecasting methods are vital in this process, predicting future energy demands and adjusting supply accordingly. Incorrect predictions can lead to increased costs and wasted energy [4]. For example, in 1984, a 1% error in energy forecasting for a UK residential building resulted in a £10 million annual loss [5]. Therefore, accurate demand forecasting is necessary for effective decision-making. Numerous forecasting methods are already being applied to both residential and industrial sectors [6]. Load forecasting systems are utilized in several practical scenarios, such as day-ahead residential forecasting, which helps to optimize energy consumption from smart grids [7]. Innovative computational methods in load forecasting are essential for tackling the energy crisis and promoting environmental sustainability [8]

LSTM, a variant of Recurrent Neural Networks (RNNs), is widely employed not just in energy forecasting but also in various computer vision tasks, including video analysis [9]. Furthermore, hybrid methodologies that combine fuzzy neural systems with genetic algorithms are commonly found in energy forecasting research [10]. For instance, Kim and Cho explored how to integrate spatial and temporal features for predicting energy use in residential settings [11]. They demonstrated the superiority of Convolutional Neural Networks (CNNs) in extracting key features influencing energy predictions, significantly reducing error rates in household power consumption datasets [12].

Despite extensive research, several challenges remain in the field of load forecasting [13]. Achieving precise forecasting accuracy remains one of the most significant challenges [14]. IoT devices, even with limited resources, have shown promising results in areas like video analytics and healthcare. A major challenge in forecasting methods, particularly for short-term load forecasting (STLF), is reducing time complexity [15]. Although cloud and fog computing hold significant promise for facilitate real-time decision-making, such as detecting abnormal energy using in this domain is still limited [16].

Moreover, machine learning has become crucial in various IoT and mobile applications, effectively extracting valuable insights from numerous sensors and scattered data in the physical world [17]. This technology excels at managing large, noisy datasets to derive actionable information, which is essential for the development of future IoT devices and services [18]. Figure 1 illustrates IoT applications in various fields.

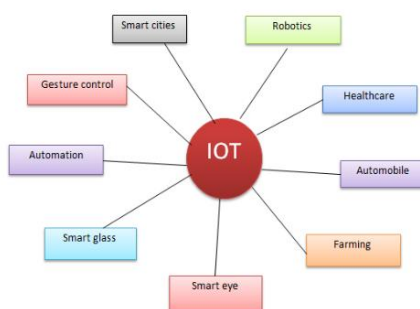


Fig 1: Internet of Things Applications

Additionally, IoT is vital in contemporary industries, as it enhances automation and helps lower operational costs. By incorporating IoT sensors into industrial processes, operators can achieve near real-time monitoring of equipment with improved reliability [20]. Research aimed at creating an EIoT applications, particularly through the use of deep learning techniques like Bayesian Neural Networks (BNN) and the Dragonfly Algorithm.

Key contributions include:

- The proposed approach reduces energy consumption by utilizing a combination of Bayesian Neural Networks and the Dragonfly Algorithm.
- The research highlights how the integration of BNN and the Dragonfly Algorithm creates a highly adaptable system, capable of adjusting to various environmental conditions, ensuring optimal energy efficiency in a range of scenarios.
- The study evaluates its results by comparing them with existing methods, using metrics such as MSE, MAPE, RMSE, and MAE.

In summary, this research makes meaningful contributions to the intelligent and energy-efficient design of Micro Electric IoT applications by incorporating cutting-edge deep learning techniques.

2. Related Works

R.A. Khalil et al. [21] proposed the role of deep learning (DL) within the Internet of Things (IoT) landscape. The authors highlight use cases of DL in Industrial IoT (IIoT), focusing on smart manufacturing, metering, and agriculture. They also identify challenges in designing and implementing DL-IIoT systems and propose future research directions to stimulate further inquiry in this area.

R. Han et al. [22] developed a framework enabling edge devices to connect with a cloud server in an IoT network. Their approach includes preprocessing methods to handle various electricity data types and implements a decision-making algorithm for short-term forecasting, which was evaluated on resource-constrained devices. The results showed a reduction in both residential and commercial datasets.

X. Wang et al. [23] conducted a thorough examination of energy efficiency across different processor cores, focusing on optimizations for varying network sizes. Their study evaluated parallel speedups and identified performance degradation resulting from overhead and memory transfers. Experimental tests with a self-sustaining wearable multisensor bracelet achieved microsecond-level latency with power consumption around a few milliwatts.

S. Zhu et al. [24] presented an intelligent edge computing framework featuring a heterogeneous architecture designed to offload AI tasks from servers. To enhance energy efficiency across computing resources, they introduced a novel algorithm for AI task scheduling. Their findings, validated through a small-scale testbed, indicated that the AI-driven IIoT applications achieved significant energy savings.

Y. Xiao et al. [25] introduced a deep reinforcement learning-based approach to enhance energy efficiency in IoT video transmission. By utilizing a deep neural network to approximate the Q-value,

they expedited the learning process for selecting optimal transmission actions, thereby improving video performance. Theoretical analyses provided insights into performance limits and computational complexity.

P. Goswami et al. [26] tackled the issue of energy consumption in large-scale IoT systems by proposing a dynamic network architecture. They employed backpropagation and convolutional neural networks to optimize resource allocation. Simulations demonstrated that this approach minimized resource wastage from redundant data, enhanced energy efficiency across the network, and effectively preserved critical information.

W. Mao et al. [27] examined the rapid expansion of IoT systems that offer extensive sensing and computing capabilities. In the context of industrial and manufacturing applications, this area, known as Industrial IoT (IIoT), is gaining traction due to its potential to lower energy consumption and reduce environmental impact. IIoT systems, reviewing and comparing existing research to identify strengths, weaknesses, and unresolved issues, particularly regarding 5G communications and edge computing trends. Table 1 in their paper presents a literature review of this framework.

Table 1: Literature survey

AUTHORS	METHODOLOGY	FINDINGS	MERITS	DEMERITS
R. A. Khalil et al [21]	Convolutional neural networks, autoencoders, and recurrent neural networks	Smart manufacturing, smart metering, and smart agriculture	Effective design and appropriate implementation	Complexity and overfitting
R. Han et al [22]	Decision-making algorithm	Short-term forecasting implemented on resource-constrained devices	Aiming to reduce the mean squared error (MSE) and root mean squared error (RMSE) for both residential and commercial datasets.	Low memory power and battery life
X. Wang et al [23]	Cortex-m4, octa-core risc-v	In-depth examination of parallel speedups and performance declines caused by	Reduced energy consumption in relation to a single-core implementation	Cannot control higher amount of dataset

		parallelization overhead and memory transfers.		
S. Zhu et al [24]	Edge computing, novel algorithm	Optimize the scheduling of various AI tasks.	The energy efficiency of different computing resources.	Low security and privacy
Y. Xiao et al [25]	Deep neural network	Energy-efficient iot video transmission scheme	Enhance the peak signal-to-noise ratio while reducing the packet loss rate.	The devices are low powered.
P. Goswami et al [26]	Back propagation neural network (BPNN) and convolutional neural network (CNN)	Analyzes the correlation between clusters to effectively allocate resources to individual nodes within each cluster.	Data security in an IOT environment	The devices are smaller in size
W. Mao et al [27]	Edge computing	Energy-saving communication and computation methods.	Using a substantial amount of energy and contributing to a larger carbon footprint.	Implementation complexity

3. Problem Statement

As IoT applications expand, these challenges become more pressing, leading to a growing need for solutions. The framework should integrate energy-efficient algorithms and strategies to lower power consumption while maintaining or enhancing application performance. This reduces the need for constant communication with distant cloud servers, thereby saving energy and enhancing real-time performance. Deep learning models can offer advanced analytical capabilities, ensuring timely and context-aware responses to environmental changes or events in IoT applications. Micro electric IoT systems often operate in unpredictable and dynamic environments. The framework should be capable

of adapting to changing conditions, such as power fluctuations, varying network connectivity, and evolving application requirements. By tackling these issues, the proposed framework aims to support the development of more intelligent, adaptable, and energy-efficient micro electric IoT applications, advancing smart systems in resource-constrained environments.

4. Proposed Work

Our proposed work using deep learning involves optimizing the interaction of components to create a novel system that minimizes energy consumption. A core strategy involves the application of advanced deep learning techniques, specifically the Bayesian Neural Network (BNN) combined with the Dragonfly Algorithm. Below is the proposed algorithmic framework that balances intelligence and energy efficiency within the micro EIoT context:

4.1 Data Collection

Collecting data is essential to clearly define the types of data needed, including sensor readings, environmental factors, power consumption metrics, and other relevant information. Next, selecting appropriate sensors and devices capable of capturing the required data is crucial, particularly when considering the power and processing limitations of micro electric environments. Once suitable devices are chosen, they should be deployed in the target environment, with proper placement to ensure representative data collection that accurately reflects real-world conditions. Data logging mechanisms must be implemented to record information efficiently, while an appropriate storage solution should be chosen to accommodate the data volume, given the limited resources of micro electric devices. Ensuring data security and privacy is equally important, especially for sensitive applications, and compliance with privacy regulations is necessary when collecting and storing data. This minimizes the need for frequent communication with distant servers, conserving energy and improving responsiveness. Additionally, enhancing the collected data with contextual information, such as geographic location and timestamps, adds valuable insight for analysis. It is also critical to implement data quality control mechanisms to detect and address any anomalies or errors, ensuring the accuracy of the deep learning models trained on this data. Continuous monitoring of the data collection process, along with regular sensor maintenance and calibration, will help ensure ongoing data accuracy and reliability. Finally, for supervised learning applications, it is important to properly label the collected data to facilitate effective training and validation of the deep learning models.

4.2 Data Pre-Processing

Pre-processing data is important to ensure data quality and model performance. First, it's essential to address any missing or null values in the dataset, either by imputing them or removing incomplete records to preserve data integrity. Noise reduction techniques, such as smoothing or filtering, should be applied to minimize any disruptions in sensor readings common in micro electric environments. Feature engineering, which involves creating or transforming features to reveal important patterns, is another important step that can significantly enhance model performance. Categorical variables should be encoded using methods like one-hot or label encoding to make them compatible with deep learning models. It's also important to identify and remove redundant or irrelevant features that may not contribute meaningfully to the model, simplifying the process and reducing computational demands. For time-sensitive data, ensuring that timestamps are synchronized across multiple sensors

will help ensure accuracy in analysis. Outliers in the dataset, which can negatively impact training, should either be removed or transformed to mitigate their effects. Finally, pre-processing must take into account the computational and memory limitations of edge devices, optimizing algorithms to function efficiently

4.3 Bayesian Neural Network

Design lightweight Bayesian Neural Network (BNN) models specifically for the limited computational resources of micro electric IoT devices. Dynamically adjust learning rates based on model performance to ensure efficient convergence and reduce unnecessary computational overhead. Optimize the inference process of BNNs to suit resource-constrained environments by employing techniques such as approximate inference or efficient sampling methods, which lower computational demands without sacrificing accuracy. Implement selective data sampling to prioritize the most informative data points during training, thereby reducing training time and computational requirements while preserving model effectiveness.

Leverage edge computing to enable localized data processing, minimizing reliance on distant servers. Incorporate energy-aware training methods into BNN development, factoring energy consumption into the optimization process to create models that are both accurate and energy-efficient for deployment. Utilize the probabilistic features of BNNs to enable intelligent sleep scheduling, predicting low-activity periods using uncertainty estimates, and scheduling sleep modes during these times to conserve energy. Opt for energy-efficient activation functions within the BNN architecture, as some are less computationally intensive and better suited for devices with limited resources. Additionally, integrate smart data compression techniques that align with the probabilistic characteristics of BNNs, further enhancing energy efficiency. Figure 2 illustrates the proposed diagram of this framework.

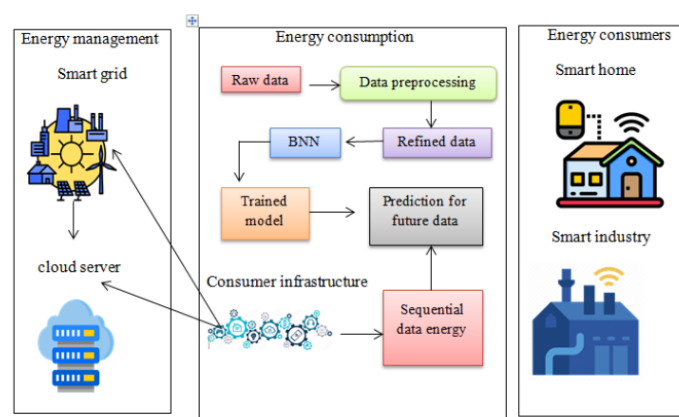


Fig 2: Proposed diagram

There are multiple ways to define a Bayesian network. Let $G = (V, E)$ represent a directed acyclic graph (DAG), and $X = (X_v)$, where $v \in V$, be a set of random variables indexed by V . According to the factorization definition, X is a Bayesian network with respect to G if its joint probability density function can be expressed as the product of individual density functions, each conditioned on its parent variables.

$$q(u) = \prod_{u \in U} q(y_u / y_{pa(u)}) \quad (1)$$

where $qa(u)$ is the set of parents of u (i.e. those vertices pointing directly to u via a single edge).

For any set of random variables, the probability of any member of a joint distribution can be calculated from conditional probabilities using the chain rule as follows:

$$Q(Y_1 = y_1, \dots, Y_n = y_n) = \prod_{u=1}^n Q(Y_u = y_u / Y_{u+1} = y_{u+1}, \dots, Y_n = y_n) \quad (2)$$

Using the definition above, this can be written as:

$$Q(Y_1 = y_1, \dots, Y_n = y_n) = \prod_{u=1}^n Q(Y_u = y_u / Y_j = y_j) \text{ for each } Y_j \text{ that is a parent of } Y_u. \quad (3)$$

The difference between the two expressions is the conditional independence of the variables from any of their non-descendants, given the values of their parent variables.

Local Markov property

X is a Bayesian network with respect to G if it satisfies the *local Markov property*: each variable is conditionally independent of its non-descendants given its parent variables:

$$Y_u \perp\!\!\!\perp Y_{U \setminus de(u)} / Y_{qa(u)} \text{ for all } u \in U \quad (4)$$

where $de(u)$ is the set of descendants and $U \setminus de(u)$ is the set of non-descendants of u .

This can be expressed in terms similar to the first definition, as

$$Q(Y_u = y_u / Y_i = y_i \text{ for each } Y_i \text{ that is not a descendant of } Y_u) \quad (5)$$

$$Q(Y_u = y_u / Y_j = y_j \text{ for each } Y_j \text{ that is not a descendant of } Y_u) \quad (6)$$

The set of parents is a subset of the set of non-descendants because the graph is acyclic.

By combining these strategies, you can develop an intelligent, energy-efficient framework using Bayesian Neural Networks for micro electric IoT applications, minimizing power consumption while maintaining high performance

4.4 Optimization

In this research, the Dragonfly Optimization Algorithm (DOA) was employed to improve the performance of an intelligent and energy-efficient framework for micro electric Internet of Things (IoT) applications by fine-tuning its hyperparameters. The DOA draws inspiration from the dynamic and static swarming behaviors of dragonflies, which encapsulate two essential phases of meta-heuristic optimization: exploration and exploitation.

In nature, dragonflies form sub-swarms that explore various regions within a static swarm, a behavior that is ideal for the exploration phase. In contrast, during the exploitation phase, dragonflies unite into large swarms and focus on a single direction. This swarming behavior adheres to three fundamental principles: separation, alignment, and cohesion, all aimed at ensuring survival. Dragonflies are attracted to food sources while avoiding threats.

In this model, the DOA is utilized to determine the optimal sequence of hyperparameters to facilitate credit card fraud detection. The process begins by initializing the dragonflies, with each one representing a potential set of hyperparameters, as detailed in Equation (8).

$$Q_n = |a_{d1}, a_{d2}, \dots a_{dg} | \quad (8)$$

Where Q_n represents the dragonfly population with size g and a_d denotes the dragonfly present in the population representing the hyperparameter sequence.

Subsequently, the fitness value of each dragonfly is assessed. In the developed model, the fitness value indicates the performance of the neuro-fuzzy algorithm, encompassing metrics such as precision, recall, and F-measure. For each dragonfly (representing a set of hyperparameters), the algorithm calculates the fitness value to maximize it. As the positions of the dragonflies are adjusted within the search space, their fitness values are updated accordingly. The mathematical representation of the adjustment in the dragonfly's position is provided in Equation (9).

$$Q_{ad}(n + 1) = (uU_r + vV_r + wW_r + dD_r + fF_r) + z_i Q_{ad}(n) \quad (9)$$

Where $Q_{ad}(n + 1)$ indicates the revised position of the dragonfly, $Q_{ad}(n)$ denotes the position of the dragonfly at n^{th} iteration, U_r indicates separation of r^{th} dragonfly, u denotes the separation weight, v represents the alignment weight, V_r refers to alignment of r^{th} dragonfly, W_r defines the cohesion of r^{th} dragonfly, w represents the cohesion weight, d denotes the food factor, D_r represents the food source of r^{th} dragonfly, f defines the enemy factor, F_r denotes the enemy position of r^{th} dragonfly, and z_i denotes the weight inertia. The calculation of separation, alignment, and cohesion is expressed in Eqn. (10), (11), and (12).

$$U_r = -\sum_{i=1}^m Q_{ad} - Q_{adi} \quad (10)$$

$$V_r = \frac{\sum_{i=1}^m F_i}{z} \quad (11)$$

$$W_r = \frac{\sum_{i=1}^m Q_{adi}}{z} - Q_{ad} \quad (12)$$

Where Q_{adi} denotes the position of i^{th} neighboring individual, Q_{ad} represents the current individual, while z denotes the number of neighboring individuals. Following this, the fitness values for the updated dragonflies (sets of hyperparameters) were calculated, and the sequence with the highest fitness value was selected. This optimization process continues until either the maximum number of iterations is reached or convergence occurs. Figure 3 presents the flowchart outlining the proposed method.

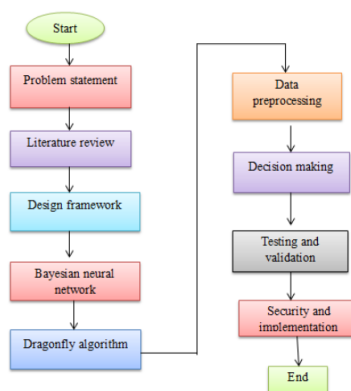


Fig 3: Flowchart of the proposed approach

The framework integrates advanced deep learning techniques, probabilistic modeling with BNNs, and the nature-inspired adaptive capabilities of the Dragonfly Algorithm. This synergy aims to minimize energy consumption, enhance predictive analytics, and optimize resource allocation in micro electric IoT ecosystems.

5. Result

The success of this integrated approach relies on the unique features of the micro EIoT application, the quality of the data, and the effective combination of Bayesian Networks with the Dragonfly Algorithm. Ongoing monitoring, assessment, and possible adjustments to the framework are crucial for maintaining optimal performance in practical situations. Here are some potential outcomes and advantages:

5.1 Performance Testing

Evaluating the effectiveness of the proposed work using deep learning involves comprehensive performance testing and assessing training accuracy. Performance testing focuses on measuring energy consumption during both training and inference across IoT devices, ensuring energy reduction without compromising system performance. Key metrics include execution time, latency, scalability under varying IoT device loads, and the efficiency of optimization algorithms, particularly the Dragonfly Algorithm, in minimizing energy consumption and enhancing the accuracy of Bayesian Neural Networks (BNNs).

Additionally, training accuracy is evaluated through classification accuracy on training and testing datasets, tracking the loss function, ensuring model convergence with minimal epochs, and validating accuracy to avoid overfitting. Energy-aware accuracy compares performance with and without energy optimizations to maintain high accuracy while reducing energy usage. These tests will demonstrate the framework's success in balancing energy efficiency and computational performance for micro EIoT systems. Figure 4 displays the training and testing accuracy of the proposed model.

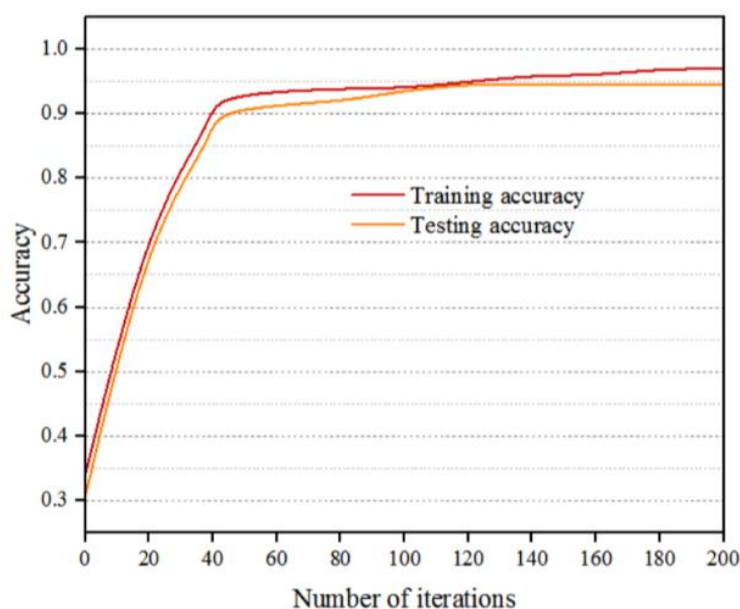


Fig 4: Testing and Training accuracy

Performance testing and training loss are critical to evaluating the effectiveness of the smart and energy-efficient framework for micro Electric IoT applications leveraging deep learning. Performance testing focuses on optimizing energy consumption while maintaining computational efficiency. Key metrics include energy usage during training and inference, execution time, latency, scalability, and the efficiency of optimization algorithms like the Dragonfly Algorithm. These metrics help assess the system's ability to reduce energy consumption while ensuring high performance. Figure 5 represent testing and training loss of the proposed model.

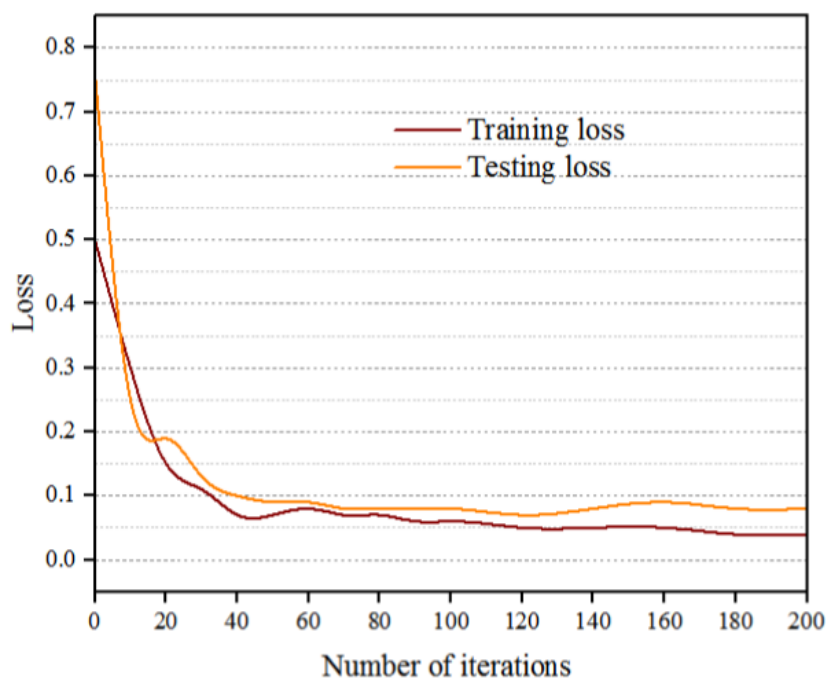


Fig 5: Testing and Training loss

On the other hand, training loss evaluates how well the model learns and improves its predictions. Key aspects of training loss include the value of the loss function, convergence rate, validation loss, and energy-aware loss, all of which are crucial for balancing learning accuracy and energy efficiency. The expected results are reduced energy consumption, faster and more efficient training, and minimized training and validation losses, indicating the model's accuracy and generalization capabilities. Overall, assessing both performance and training loss will demonstrate how well the framework meets its objectives of energy efficiency and computational performance in micro Electric IoT systems

5.2 Dataset Structure

5.2.1 Temperature

Tracking temperature is offers valuable information about environmental conditions, equipment status, and overall system efficiency. Select a suitable temperature sensor tailored to the specific needs of your application. Common types include thermocouples, thermistors, and infrared sensors. Figure 6 shows that the temperature of various existing models.

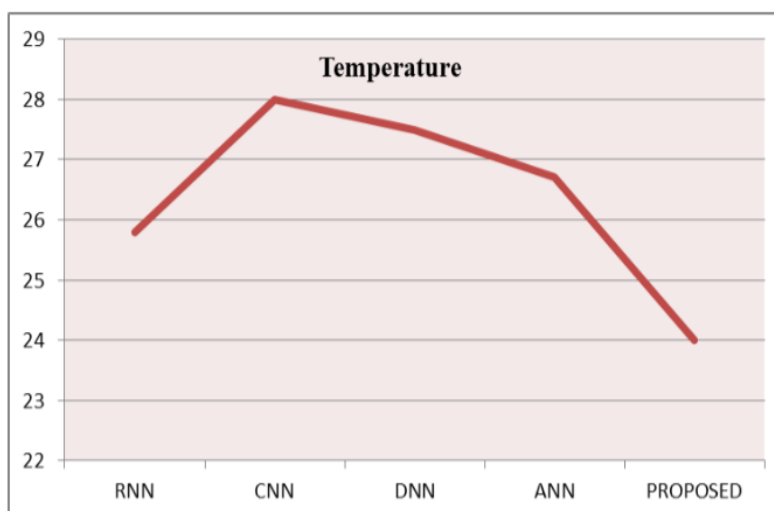


Fig 6: Temperature

5.2.2 Humidity

Humidity monitoring is a Micro Electric Internet of Things (EIoT) applications, especially those involving environmental sensing, agriculture, HVAC systems, or any scenario where humidity levels play a significant role. Monitoring humidity in micro EIoT applications is essential for maintaining optimal conditions, ensuring the proper functioning of devices, and supporting various applications. Figure 7 shows that the humidity of existing work.

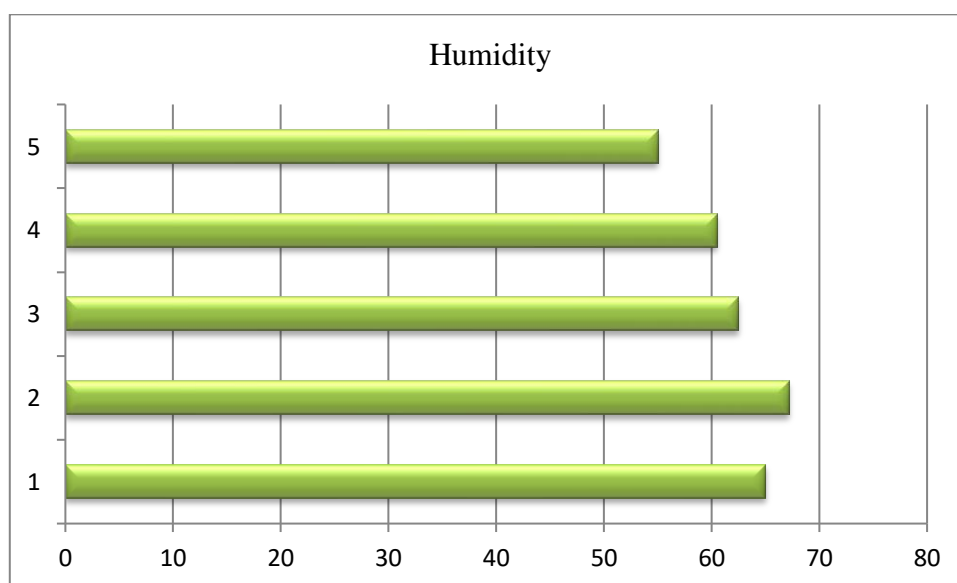


Fig 7: Humidity

5.2.3 Light intensity

Monitoring light intensity in a Micro Electric Internet of Things (EIoT) is essential for various scenarios, such as smart lighting, agriculture, and environmental sensing. Figure 8 shows that comparison of light intensity of existing techniques.

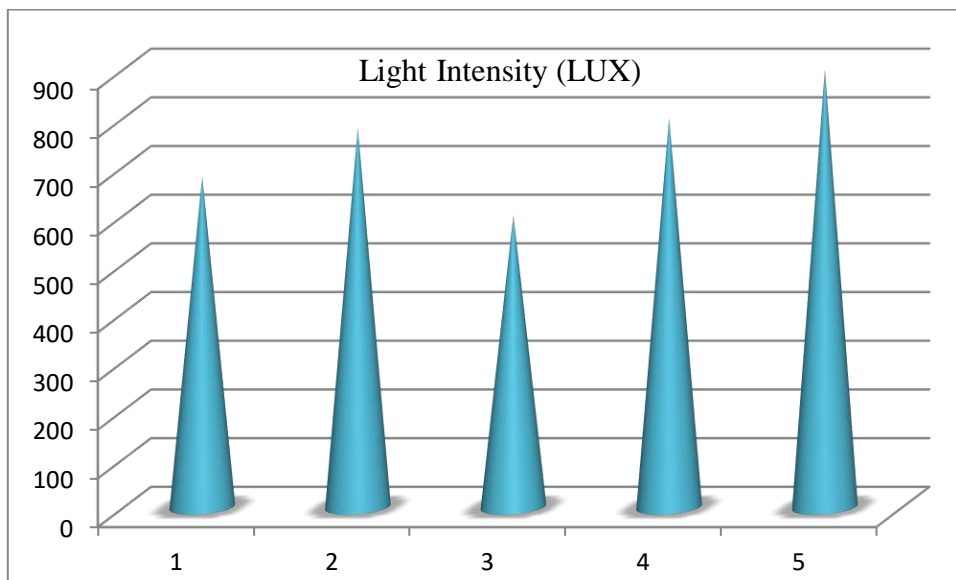


Fig 8: Light Intensity

5.2.4 Voltage levels

The micro EIoT device operates on a battery, making it important to monitor voltage levels to assess battery life and decide when replacement is needed. Customize your approach to fit the specific needs of your micro EIoT application. Tracking voltage is critical for maintaining device health and performance, and a strong monitoring system can enhance the reliability and durability of your micro EIoT devices. Figure 9 represents voltage levels of various existing models.

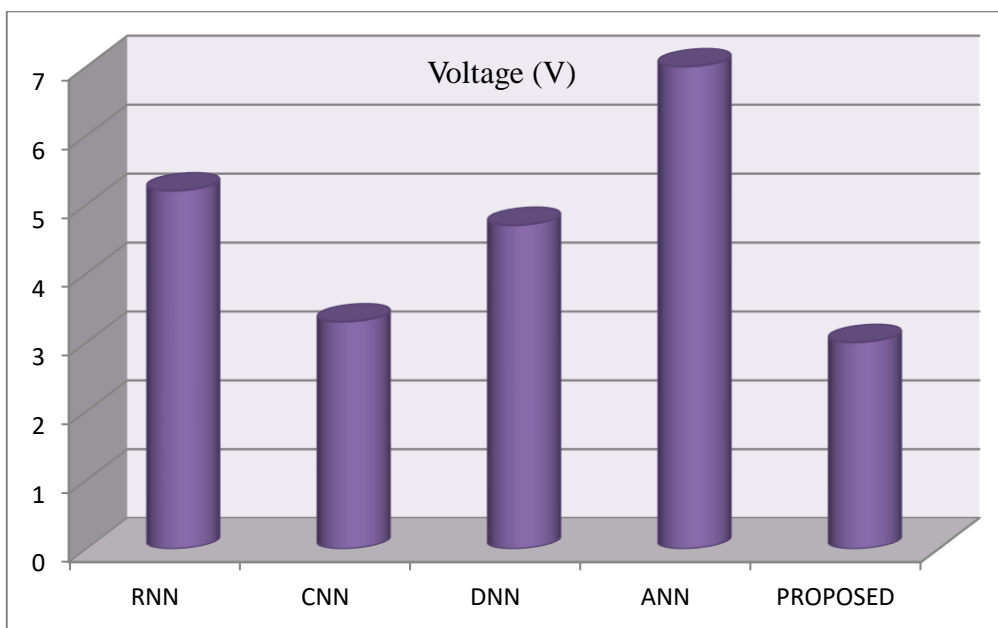


Fig 9: Voltage levels

5.2.5 Energy consumption

Monitoring energy consumption in a Micro Electric Internet of Things (EIoT) application is vital for optimizing resource usage, predicting battery life, and ensuring efficient operation. Here's a guide on

how to incorporate energy consumption monitoring into your micro EIoT application: For battery-powered micro EIoT devices, monitoring energy consumption is critical for predicting battery life and optimizing sleep modes or duty cycles to extend the device's operational time between battery replacements or recharges. Figure 10 shows that energy consumption of various existing models.

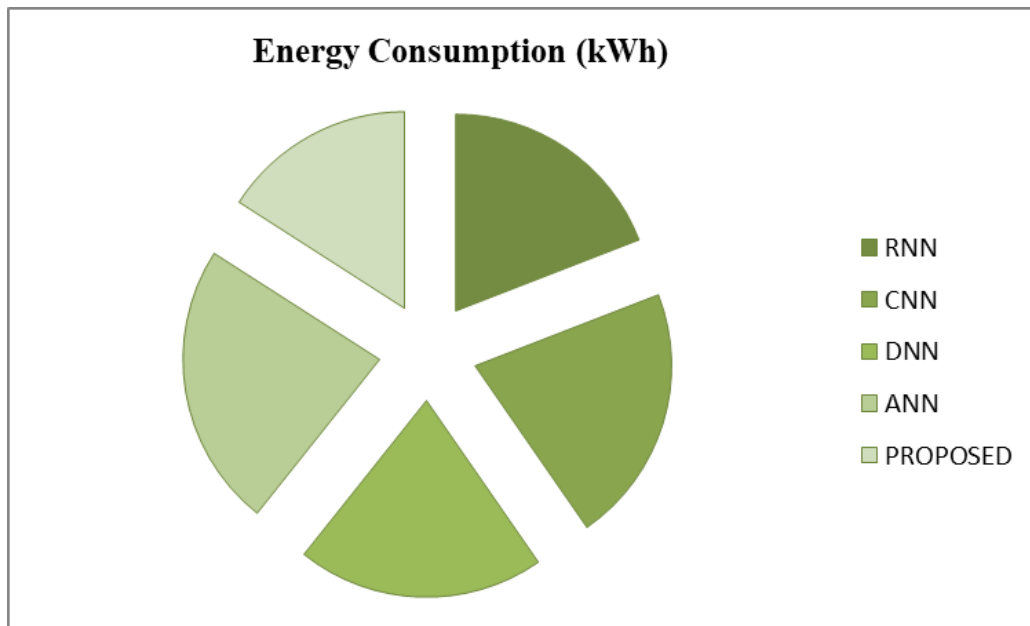


Fig 10: Energy consumption

Energy consumption monitoring is fundamental for efficient resource management and can contribute significantly to the sustainability and longevity of your micro EIoT devices. Table 2 illustrates the data structure of existing methods.

Table 2: Dataset Structure

Method	Temperature	Humidity	Light Intensity (LUX)	Voltage (V)	Energy Consumption (kWh)
RNN	25.8	65	680	5.2	10.8
CNN	28	67.2	780	3.3	12
DNN	27.5	62.5	600	4.7	11.5
ANN	26.7	60.5	800	7	13.2
PROPOSED	24	55	900	3	9

5.3 Evaluation Metrics

For performance evaluation, metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are used to analyze the experimental results. The mathematical expressions for these metrics are as follows:

$$MSE = \frac{1}{m} \sum_1^m (x - \hat{x})^2 \quad (13)$$

$$MAE = \frac{1}{m} \sum_1^m |x - \hat{x}| \quad (14)$$

$$RMSE = \sqrt{\frac{1}{m} \sum_1^m (x - \hat{x})^2} \quad (15)$$

$$MAPE = \frac{100\%}{m} \sum_{t=1}^m \left| \frac{P_t - Q_t}{P_t} \right| \quad (16)$$

The MSE metric calculates the average squared difference between the actual and predicted values, capturing the overall magnitude of prediction errors (Equation 13). MAE, on the other hand, measures the average absolute difference between predictions and actual values, providing insight into the average size of errors without accounting for their direction (Equation 14). RMSE is widely used in fields like forecasting and regression analysis to assess the standard deviation of prediction errors, helping to evaluate model performance (Equation 15). Finally, MAPE quantifies the accuracy of a model’s predictions, especially in forecasting tasks, by expressing the error as a percentage (Equation 16).

5.4 Performance Comparison

We assess the performance of our proposed approach by comparing it with competitive benchmarks using datasets from both individual household electricity consumption and commercial data sources. The upcoming sections provide an in-depth comparison with modern techniques across residential and commercial datasets, emphasizing the benefits of our model. On the UCI dataset. Figure 11 presents a comparison of the MSE values between our method and existing techniques.

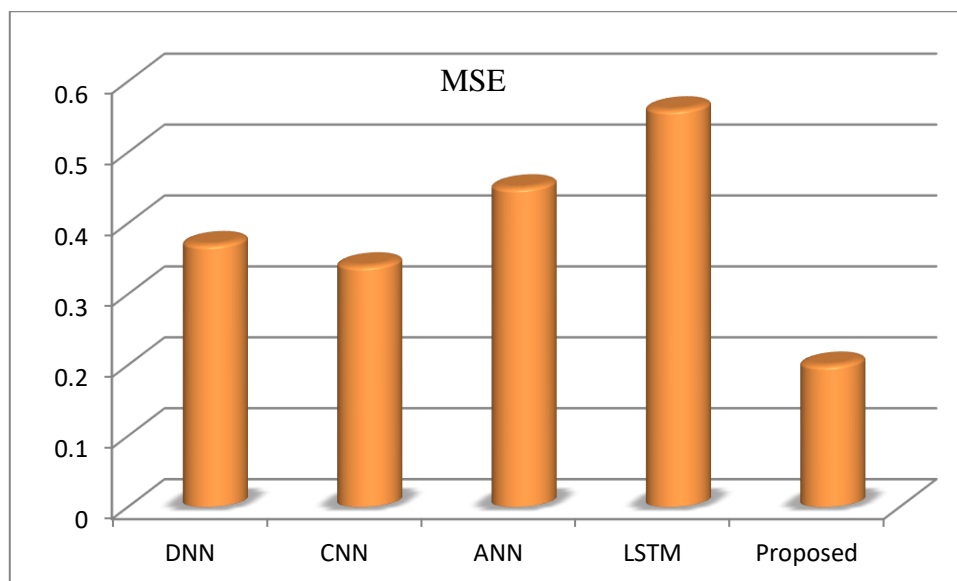


Fig 11: Comparing MSE with existing techniques

In comparison to established models like DNN, CNN, ANN, and LSTM networks, our proposed model attained mean squared error (MSE) rates of 0.37, 0.34, 0.45, 0.56, and 0.20, respectively. MSE, also referred to as mean squared deviation (MSD), measures the average of the squared differences between predicted values and actual outcomes.

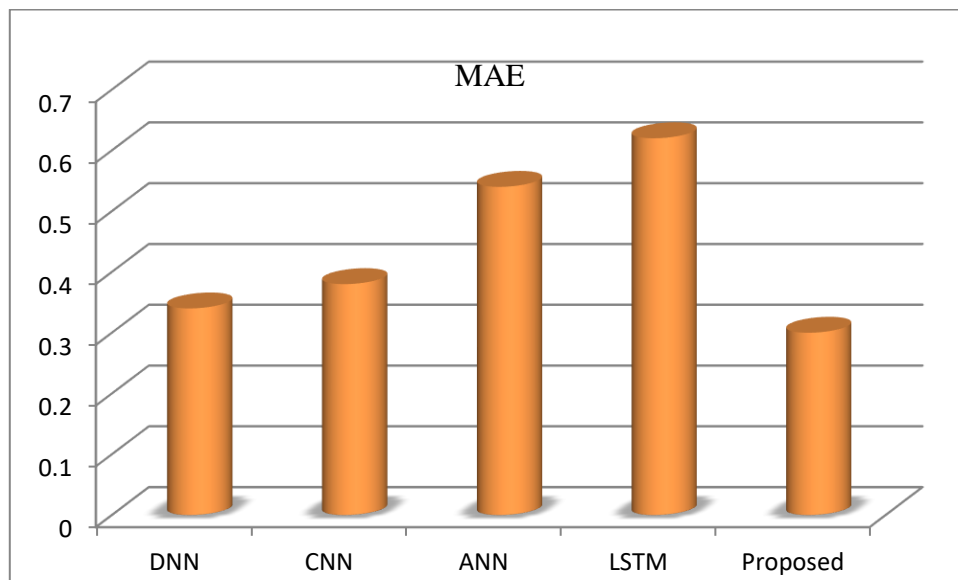


Fig 12: Comparing MAE with existing techniques

When compared to established models such as DNN, CNN, ANN, and LSTM networks, our proposed model recorded mean absolute error (MAE) rates of 0.34, 0.38, 0.54, 0.62, and 0.30, respectively. The mean absolute error is a widely used metric for assessing forecasts against actual results, offering an overview of performance without accounting for whether predictions are above or below the true values. In contrast, the mean signed difference highlights the direction of the errors. Figure 12 illustrates the comparison of MAE values among the different techniques.

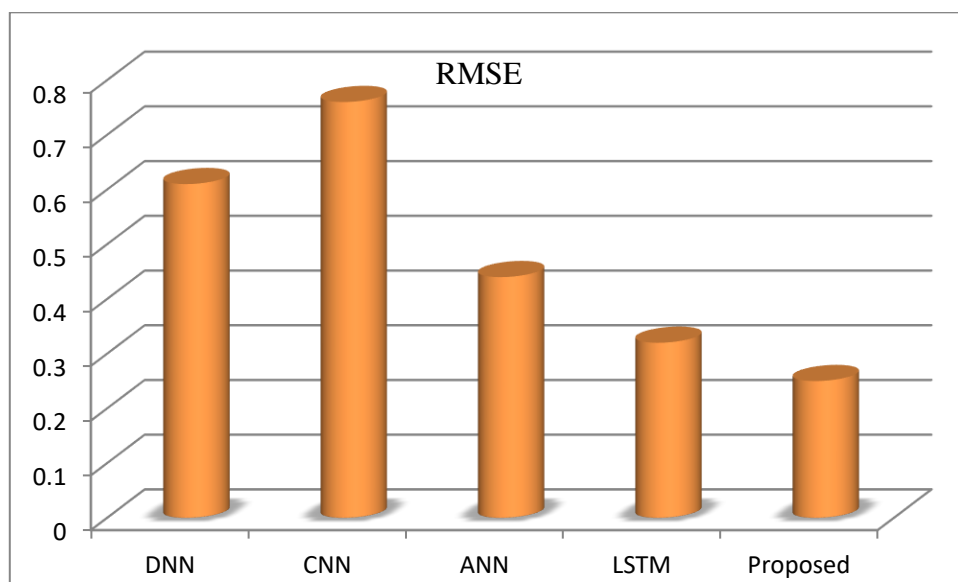


Fig 13: Comparing RMSE with existing techniques

When compared to established models like DNN, CNN, ANN, and LSTM networks, our proposed model demonstrated root mean square error (RMSE) rates of 0.61, 0.76, 0.44, 0.32, and 0.25, respectively. RMSE is a commonly utilized metric for evaluating the precision of models and algorithms, particularly in regression analysis and predictive tasks. A comparison of the RMSE values is illustrated in Figure 13.

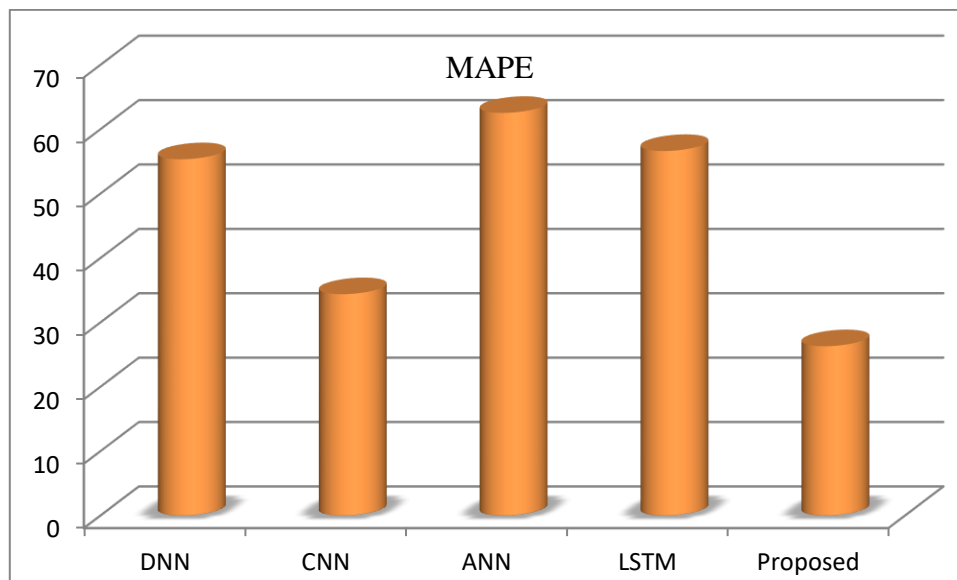


Fig 14: Comparing MAPE value with existing techniques

In comparison to existing models such as DNN, CNN, ANN, and LSTM-based networks, the proposed model demonstrated error rates of 55.34%, 34.38%, 62.54%, 56.62%, and 26.30% for MAPE, respectively. Figure 14 illustrates the comparison of MAPE values. The proposed models exhibits lower computational complexity, and when comparing the predicted power to the ground truth values, only minor variations are observed. This suggests the model's effectiveness for real-world applications. Table 3 presents a comparative evaluation of the system's performance.

Table 3: Comparative analysis of system performance

METHOD	MSE	MAE	RMSE	MAPE
DNN	0.37	0.34	0.61	55.34
CNN	0.34	0.38	0.76	34.38
ANN	0.45	0.54	0.44	62.54
LSTM	0.56	0.62	0.32	56.62
Proposed	0.20	0.30	0.25	26.30

6. Discussion

We carry out extensive experiments that include comparisons with leading-edge methods across two distinct datasets, while also evaluating time complexity for both personal computers (PCs) and devices with limited resources. The datasets utilized for these comparisons consist of individual household electric power consumption and a commercial dataset. Our findings highlight the superior performance of our multilayered GRU model, which exceeds the capabilities of recent methods

found in the energy forecasting literature. This section will begin with a discussion of the evaluation metrics used in our analysis.

7. Conclusion

This study introduced an innovative framework aimed at tackling the significant issue of energy consumption in micro electric Internet of Things (IoT) applications. By combining cutting-edge deep learning methods, particularly Bayesian Neural Networks (BNN), with the flexible optimization features of the Dragonfly Algorithm, the framework showed great potential in delivering intelligence, efficiency, and adaptability. This innovative framework addresses key challenges in terms of energy consumption, intelligent decision-making, and optimizations. The Dragonfly Algorithm's optimization allocating resources effectively, operate devices at their peak efficiency levels while minimizing unnecessary energy consumption. This is particularly valuable in EIoT scenarios where environmental conditions and operational requirements may vary. The focus on energy efficiency aligns with broader sustainability goals, contributing to reduced energy consumption. The combination of Bayesian Neural Networks and the Dragonfly Algorithm provides a foundation for real-time decision support in EIoT applications

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