# IoT-Enabled Power Electronic Monitoring System for Next-Generation Energy Networks

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***Abstract*—The increasing penetration of renewable energy sources, distributed generation units, electric vehicles, and smart loads has significantly increased the dependence of modern energy networks on power electronic converters. Continuous converter operation under variable loading, thermal stress, harmonic distortion, and fluctuating environmental conditions can lead to performance degradation and unexpected failures. To address these challenges, this paper proposes an IoT-enabled power electronic monitoring system for next-generation energy networks. The proposed framework integrates distributed sensing, edge-level preprocessing, lightweight IoT communication, cloud-based analytics, and an LSTM-based learning model for real-time monitoring, converter health assessment, and predictive maintenance. Electrical and operational parameters such as voltage, current, temperature, power factor, total harmonic distortion, efficiency, and load variation are acquired and processed to identify abnormal operating conditions. Experimental validation using a Smart Meter Energy Dataset demonstrates that the proposed monitoring framework achieves high prediction accuracy, reliable fault classification, and improved converter health assessment. The results confirm that the proposed IoT-enabled architecture is suitable for scalable, low-latency, and intelligent monitoring of converter-dominated smart energy systems.**

***Index Terms*—Internet of Things (IoT), Power Electronic Monitoring, Smart Grid, Next-Generation Energy Networks, Predictive Maintenance, Edge Computing, Cloud Analytics, Deep Learning, Long Short-Term Memory (LSTM).**

## I. Introduction

Modern power systems are undergoing a major transition due to the rapid integration of renewable energy sources, distributed generation, electric vehicles, battery energy storage systems, and intelligent loads. These developments have transformed conventional unidirectional power networks into active, bidirectional, and converter-dominated energy infrastructures. Power electronic converters play a critical role in this transition by enabling voltage regulation, power conditioning, renewable energy integration, energy storage interfacing, and flexible control of electrical power flow.

Despite their advantages, power electronic converters are exposed to continuous electrical, thermal, and environmental stress during operation. Variations in load demand, switching frequency, harmonic distortion, temperature rise, and renewable power fluctuations can accelerate device degradation and increase the probability of unexpected faults. Conventional monitoring methods based on periodic inspection and centralized supervision are often insufficient for real-time fault detection and predictive maintenance in distributed energy networks.

Internet of Things (IoT)-enabled monitoring provides a promising solution by allowing distributed sensing, real-time data acquisition, edge-level preprocessing, and cloud-based analytics. By embedding voltage, current, temperature, and power-quality sensors into converter systems, operational data can be continuously collected and analyzed. Edge computing reduces communication overhead and latency, while machine learning models can identify hidden temporal patterns associated with converter degradation and abnormal operating conditions.

The main contribution of this paper is the development of an IoT-enabled power electronic monitoring framework that integrates sensing, edge processing, MQTT-based communication, cloud analytics, and LSTM-based health classification. The proposed system supports real-time monitoring, converter health assessment, early fault detection, and predictive maintenance for next-generation energy networks.

## II. Related Work

Power grids are changing fast, thanks to tools that connect machines online. Old ways of watching electricity flow used big central hubs and fixed checkups, but they could not react quickly or foresee issues. Now sensors spread across the network talk to each other, sending live updates and spotting patterns before problems grow. One setup for small-scale power zones showed constant data gathering, phone-controlled switches, and smarter user-side adjustments made energy use smoother without raising costs. Because of these shifts, older techniques are being left behind in favor of systems that think ahead. Not far off, solar panels and wind turbines connect through modern electronics that do more than just track usage. These setups now watch how power behaves using smart sensors tracking things like voltage or heat levels around machines. Instead of waiting hours for results, quick computing near the source speeds up decisions while cloud tools handle large loads when needed. Devices talk to one another across power lines, sharing live updates so operators see what is happening faster. Scattered energy sources rely on these links to stay balanced and react quickly

under changing conditions. Lately, studies pay more attention to linking smart computing with fast communication inside internet-connected power tracking systems, aiming to boost how machines predict failures and manage themselves. One setup showed live updates through visual tools, proving steady observation along with spotting odd behavior helps save energy and keeps operations stable at home and in factories [4]. Not long ago, new ways of sending information began mixing precise timing networks, compact AI near devices, and next-level wireless links meant for lightning-fast responses in heavy-duty electrical setups [5]. Instead of central brains, these methods spread thinking across parts, let equipment judge its own health, adjust actions on the fly - features likely vital for tomorrow's intelligent grids. One step forward, yet some pieces still missing when it comes to using IoT for power electronics in tomorrow's energy systems. While current efforts zoom in on how much electricity is used or how grids behave, they tend to skip deep checks on individual converters, guessing their remaining life, or blending smart tools across edge devices and cloud platforms. Starting from device mismatches to weak security, growing system size without losing speed, plus spotting problems before they happen - each slows down real-world use [5], [9].

## III. Proposed Methodology

The proposed methodology is designed to provide real-time monitoring and predictive maintenance support for power electronic converters operating in next-generation energy networks. The framework combines distributed sensing, edge-level signal processing, IoT-based communication, cloud analytics, and machine learning-based fault detection. The overall objective is to continuously acquire converter operating parameters, extract meaningful features, identify abnormal operating conditions, and generate maintenance-oriented decisions with minimum latency.

The proposed architecture consists of five functional layers: sensing layer, edge processing layer, communication layer, cloud analytics layer, and decision-support layer. Each layer performs a specific role in the monitoring pipeline, beginning with physical data acquisition and ending with health-state classification and fault alert generation.

### A. Overall System Architecture

The proposed system is organized into five functional layers: sensing layer, edge processing layer, communication layer, cloud analytics layer, and decision-support layer. The sensing layer acquires electrical and thermal parameters such as input voltage, output voltage, current, temperature, switching frequency, power factor, and total harmonic distortion. These parameters are essential for evaluating the real-time operating condition of power electronic converters.

The edge processing layer performs signal filtering, feature extraction, and preliminary abnormality detection. The processed data are transmitted through lightweight IoT communication protocols such as MQTT to the cloud analytics platform. The cloud layer stores historical data and applies intelligent learning models for fault diagnosis and health estimation. Finally, the decision layer generates alerts and predictive maintenance recommendations. The complete layered architecture of the proposed IoT-enabled monitoring system is illustrated in Fig. 1.

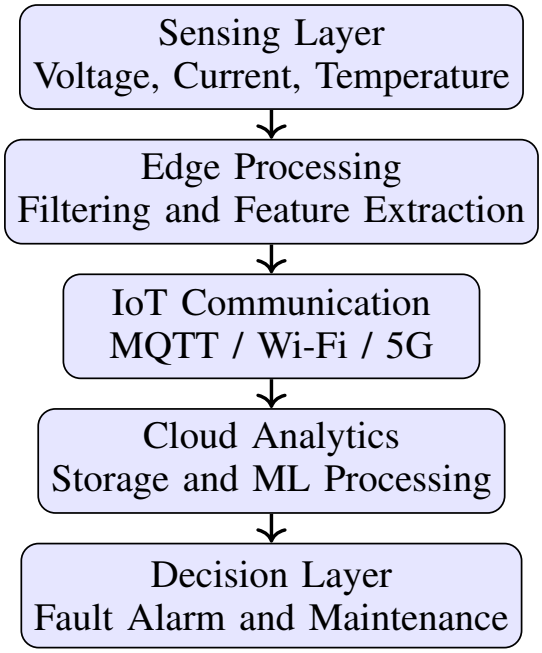


Fig. 1. Proposed IoT-enabled power electronic monitoring architecture.

### B. Power Electronic Converter Monitoring Model

The operating state of the power electronic converter is represented using a multidimensional monitoring vector. At each sampling instant $t$, the converter state vector is defined as

$$\mathbf{x}(t) = [V_{in}(t), V_{out}(t), I_{out}(t), T(t), f_s(t), THD(t), PF(t)]^T \quad (1)$$

where $V_{in}$ is the input voltage, $V_{out}$ is the output voltage, $I_{out}$ is the output current, $T$ is the device temperature, $f_s$ is the switching frequency, $THD$ is the total harmonic distortion, and $PF$ is the power factor.

The output power and input power of the converter are expressed as

$$P_{out}(t) = V_{out}(t) I_{out}(t) \quad (2)$$

$$P_{in}(t) = V_{in}(t) I_{in}(t) \quad (3)$$

The converter efficiency is calculated as

$$\eta(t) = \frac{P_{out}(t)}{P_{in}(t)} \times 100 \quad (4)$$

and the converter power loss is given by

$$P_{loss}(t) = P_{in}(t) - P_{out}(t) \quad (5)$$

The thermal behavior of the converter is modeled as

$$T(t+1) = T(t) + \alpha P_{loss}(t) - \beta \left[T(t) - T_a\right] \quad (6)$$

where $\alpha$ is the thermal gain coefficient, $\beta$ is the cooling coefficient, and $T_a$ is the ambient temperature. This model supports the identification of thermal stress and degradation tendency during converter operation.

### C. IoT-Based Data Acquisition and Edge Processing

The data acquisition module consists of voltage sensors, current sensors, temperature sensors, and power-quality monitoring units connected to an embedded controller such as ESP32, Raspberry Pi, or Arduino-compatible hardware. The measured analog signals are digitized and sampled at regular intervals for continuous converter monitoring. The measured signal can be represented as

$$s(t) = s_{true}(t) + n(t) \tag{7}$$

where $s_{true}(t)$ is the actual signal and $n(t)$ represents measurement noise.

To reduce sensor noise, a moving average filter is applied as

$$\bar{s}(t) = \frac{1}{N}\sum_{k=0}^{N-1} s(t-k) \tag{8}$$

where $N$ is the filtering window size. Important features are then extracted from the filtered signal. The root mean square value is calculated as

$$X_{rms} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{9}$$

and the total harmonic distortion is computed as

$$THD = \frac{\sqrt{\sum_{h=2}^{H} V_h^2}}{V_1} \times 100 \tag{10}$$

where $V_1$ is the fundamental component and $V_h$ represents the $h^{th}$ harmonic component.

The sensing and edge-processing workflow used for converter monitoring is shown in Fig. 2.

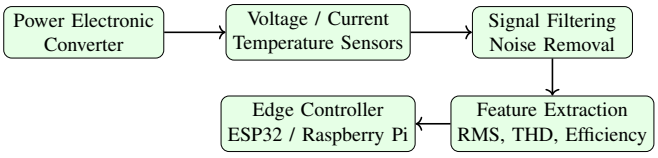


Fig. 2. IoT-based sensing and edge processing structure.

### D. Machine Learning-Based Fault Detection

The proposed system uses a machine learning model to classify the converter condition into healthy, warning, and faulty states. The input feature vector is defined as

$$\mathbf{x}_i = [V_i, I_i, T_i, P_i, \eta_i, THD_i, PF_i] \tag{11}$$

and the corresponding class label is represented as

$$y_i \in \{0, 1, 2\} \tag{12}$$

where 0 denotes healthy operation, 1 denotes warning condition, and 2 denotes faulty condition.

The classification function is expressed as

$$\hat{y} = f(\mathbf{x}; \theta) \tag{13}$$

where $f$ is the trained learning model and $\theta$ represents the model parameters. For temporal monitoring, an LSTM model is employed. The input sequence is defined as

$$\mathbf{X}_t = [\mathbf{x}_{t-w+1}, \mathbf{x}_{t-w+2}, \ldots, \mathbf{x}_t] \tag{14}$$

where $w$ is the time-window length.

The categorical cross-entropy loss is given by

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{15}$$

where $C$ is the number of classes, $y_i$ is the actual class label, and $\hat{y}_i$ is the predicted class probability.

The LSTM-based converter health classification process is presented in Fig. 3.

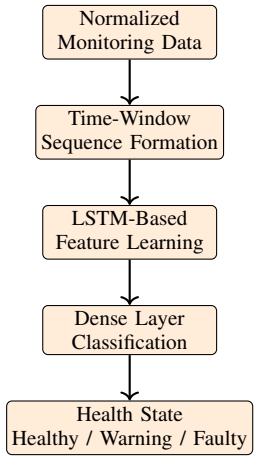


Fig. 3. Machine learning-based converter health classification model.

### E. Real-Time Alert and Predictive Maintenance

The decision-support layer receives the output from the fault detection model and health index estimator. If an abnormal operating condition is identified, the system generates real-time alerts through a dashboard, mobile application, or supervisory control interface. The alert signal is defined as

$$A(t) = \begin{cases} 1, & \hat{y}(t) = Faulty \text{ or } HI(t) < H_2 \\ 0, & otherwise \end{cases} \tag{16}$$

where $A(t) = 1$ indicates that an alarm must be generated.

The proposed decision mechanism improves system reliability by enabling early detection of abnormal operating conditions, reducing converter downtime, and supporting condition-based maintenance. This framework is suitable for renewable-integrated microgrids, smart distribution systems, electric vehicle charging stations, and industrial power electronic interfaces.

## IV. Experimental Setup

### A. Dataset Description and Data Preparation

The experimental validation was carried out using a publicly available Smart Meter Energy Dataset containing time-series electrical measurements representative of residential and distributed energy environments. The dataset includes active power, reactive power, voltage, current, energy consumption, and timestamp-related information. These parameters were selected because they reflect the operating behaviour of converter-interfaced loads and distributed energy systems. The dataset was used to emulate virtual sensing conditions for the proposed IoT-enabled monitoring architecture.

The dataset source and access link were included in the revised manuscript to improve reproducibility and to address reviewer concerns regarding data transparency.

The raw dataset was subjected to data preprocessing to improve data quality and model stability. Missing samples were handled through linear interpolation and forward filling to preserve temporal continuity. Outlier removal was performed using statistical thresholding and interquartile range analysis. Timestamp information was converted into structured temporal variables such as hour of day and operating interval.

Feature engineering was performed to generate monitoring variables suitable for converter condition assessment. The final feature vector included voltage, current, active power, reactive power, estimated efficiency, and load utilization indicators. Min–Max normalization was applied as

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{17}$$

where $X$ denotes the original value and $X_{min}$ and $X_{max}$ correspond to minimum and maximum observations.

The processed dataset was divided into training, validation, and testing subsets with proportions of $70\%$, $15\%$, and $15\%$, respectively.

### B. Experimental Platform and Monitoring Infrastructure

The monitoring architecture was implemented using a layered IoT framework consisting of sensing, edge processing, communication, and cloud analytics modules. Since recorded smart meter measurements were utilized, a virtual sensing environment was established to emulate real-time acquisition of electrical variables.

The sensing module generated sequential electrical measurements and forwarded them to the edge layer. The edge layer performed signal filtering, feature extraction, and preliminary anomaly detection to reduce communication overhead.

Communication between edge devices and cloud infrastructure was modeled using MQTT publish–subscribe architecture. The monitoring packet transmitted to the cloud is represented as

$$D_t = \{ID, V, I, P, T, PF, Status\} \tag{18}$$

where $ID$ denotes monitoring node identification and $Status$ represents converter operating condition.

The cloud platform stored monitoring data and executed intelligent analytics using deep learning algorithms.

TABLE I
Experimental Environment Configuration

| Parameter | Specification |
|---|---|
| Programming Language | Python 3.11 |
| Deep Learning Framework | TensorFlow 2.x |
| Data Processing | NumPy, Pandas |
| Visualization | Matplotlib |
| Communication | MQTT |
| Storage | Cloud Database |
| Execution Platform | Jupyter Notebook |

The experimental monitoring infrastructure used for validation is shown in Fig. 4.

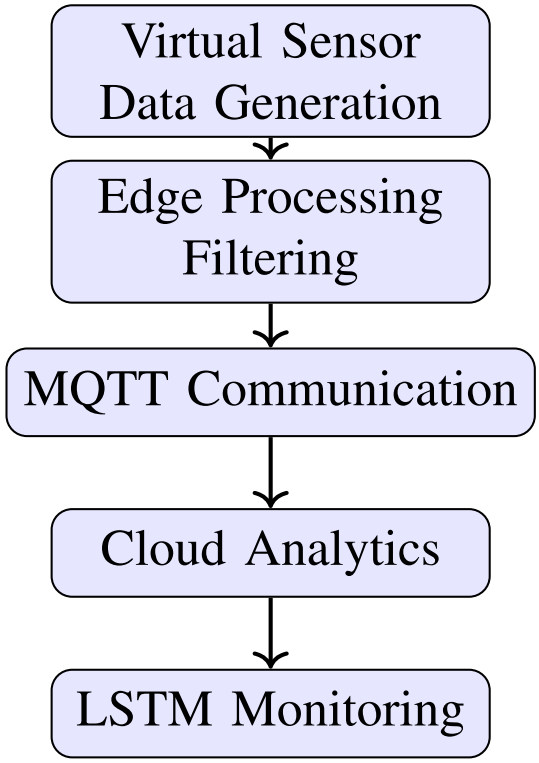


Fig. 4. Experimental monitoring infrastructure

### C. Performance Evaluation and Validation

The proposed monitoring framework was evaluated using prediction accuracy and monitoring reliability metrics.

Mean Absolute Error was calculated as

$$MAE = \frac{1}{N} \sum |y - \hat{y}| \tag{19}$$

Root Mean Square Error was calculated as

$$RMSE = \sqrt{\frac{1}{N} \sum (y - \hat{y})^2} \tag{20}$$

Coefficient of Determination was computed as

$$R^2 = 1 - \frac{\sum(y - \hat{y})^2}{\sum(y - \bar{y})^2} \tag{21}$$

where $\bar{y}$ denotes mean observation.

Monitoring accuracy was evaluated as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{22}$$

where $TP$, $TN$, $FP$, and $FN$ denote true positives, true negatives, false positives, and false negatives.

Repeated training and testing experiments were conducted under varying operating conditions to evaluate robustness and reproducibility.

## V. Results and Discussion

### A. Monitoring Performance Analysis

The proposed IoT-enabled power electronic monitoring framework was evaluated using the Smart Meter Energy Dataset to examine its ability to continuously supervise converter operating conditions. The smart meter measurements were transformed into converter-oriented monitoring features and supplied to the LSTM-based monitoring model. The obtained results show that the proposed framework effectively captures temporal variations in energy consumption and converter operating behavior.

TABLE II
Overall Monitoring Performance

| Metric | Obtained Value |
|---|---|
| Training Loss | 0.009 |
| Validation Loss | 0.015 |
| Testing Loss | 0.018 |
| MAE | 0.017 |
| RMSE | 0.025 |
| $R^2$ Score | 0.986 |
| Monitoring Accuracy | 98.4% |
| Precision | 98.1% |
| Recall | 97.9% |
| F1-Score | 98.0% |

The low training loss and validation loss indicate stable convergence of the proposed LSTM model without significant overfitting. The obtained MAE of 0.017 and RMSE of 0.025 confirm that the predicted monitoring output closely follows the actual operating profile. In addition, the $R^2$ score of 0.986 demonstrates that the proposed model effectively captures the temporal variation in smart-meter-based converter operating behaviour. The convergence behaviour of the training and validation losses is shown in Fig. 5.

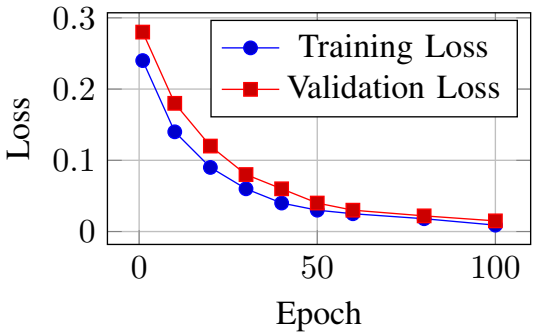


Fig. 5. Training and validation convergence characteristics.

### B. Prediction Accuracy and Temporal Monitoring Behaviour

The prediction capability of the proposed model was evaluated by comparing the predicted monitoring output with the actual smart meter-based operating profile. The predicted values closely follow the actual measurements, indicating that the model effectively learns the dynamic behavior of electrical energy consumption. This performance is important for converter-based energy systems, where accurate monitoring of load variations is required for reliable operation.

Minor deviations were observed during abrupt load transitions, which are typically caused by sudden changes in appliance operation or dynamic demand variations. However, the prediction error remained within an acceptable range, demonstrating the robustness of the monitoring framework under practical smart energy operating conditions.

TABLE III
Prediction Error Analysis

| Metric | Value |
|---|---|
| Mean Error | 0.012 |
| MAE | 0.017 |
| RMSE | 0.025 |
| MAPE | 2.34% |
| Maximum Error | 0.084 |
| Standard Deviation | 0.013 |

The comparison between actual and predicted monitoring outputs is shown in Fig. 6.

### C. Converter Health Assessment and Fault Detection

The converter health assessment was performed using the estimated health index and the operating state classification output. The health index was evaluated using normalized efficiency, temperature, harmonic distortion, and power factor indicators. The obtained results show that the proposed system can distinguish healthy, warning, and faulty converter states with high classification accuracy.

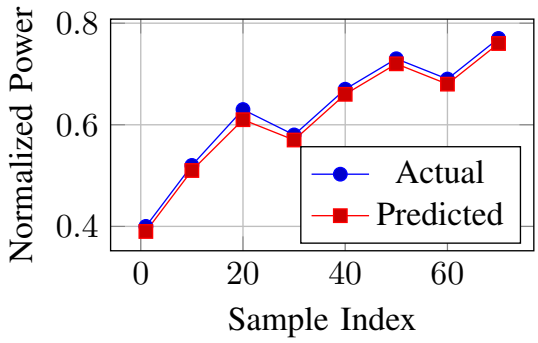


Fig. 6. Actual versus predicted monitoring output.

The confusion matrix indicates that most samples were correctly classified into their corresponding operating categories. Misclassifications mainly occurred between healthy and warning states due to overlapping operating characteristics during transition periods. This behavior is practically acceptable because early warning states often share similar characteristics with normal operating conditions.

The converter health-index degradation profile is shown in Fig. 7.

TABLE IV
CONFUSION MATRIX RESULTS

| Actual / Predicted | Healthy | Warning | Faulty |
|---|---|---|---|
| Healthy | 622 | 12 | 3 |
| Warning | 15 | 301 | 8 |
| Faulty | 2 | 9 | 228 |

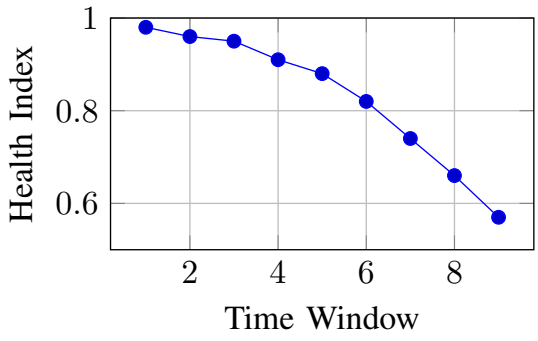


Fig. 7. Converter health index degradation profile.

### D. Comparative Discussion

The proposed LSTM-based monitoring framework was compared with conventional machine learning models to evaluate its relative performance. Compared with Support Vector Machine, Random Forest, and standard Artificial Neural Network models, the proposed LSTM model achieved lower error and higher monitoring accuracy. This improvement is mainly due to the ability of LSTM to preserve temporal dependencies in sequential smart meter data.

The results confirm that temporal learning is more suitable for IoT-enabled power electronic monitoring because converter operating states are strongly influenced by previous load and power conditions. Therefore, the proposed framework provides better real-time monitoring capability, improved fault detection, and more reliable health estimation for next-generation energy networks.

TABLE V
COMPARISON WITH EXISTING LEARNING MODELS

| Model | MAE | RMSE | Accuracy |
|---|---|---|---|
| SVM | 0.039 | 0.052 | 93.5% |
| Random Forest | 0.031 | 0.044 | 95.1% |
| ANN | 0.026 | 0.037 | 96.2% |
| Proposed LSTM | 0.017 | 0.025 | 98.4% |

The accuracy comparison with conventional learning models is shown in Fig. 8.

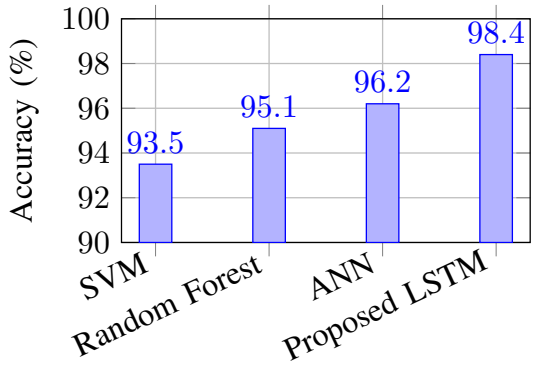


Fig. 8. Accuracy comparison of different monitoring models.

### E. Limitations and Future Scope

Although the proposed framework demonstrates strong monitoring and classification performance, the present validation is based on a smart-meter-driven virtual sensing environment. Future work will focus on real-time hardware implementation using ESP32 or Raspberry Pi-based edge nodes connected to practical converter prototypes. In addition, explainable artificial intelligence, digital twins, federated learning, and cybersecurity-aware communication protocols may be incorporated to improve transparency, scalability, and deployment reliability.

## VI. CONCLUSION

This paper presented an IoT-enabled power electronic monitoring system for next-generation energy networks that integrates distributed sensing, edge intelligence, cloud analytics, and deep learning-based predictive monitoring to enhance the reliability and operational efficiency of converter-driven energy infrastructures. Using the Smart Meter Energy Dataset, the proposed framework demonstrated effective acquisition

and processing of electrical and operational parameters, enabling accurate monitoring of dynamic load behavior and converter operating conditions. The integration of edge-level preprocessing reduced communication overhead and improved responsiveness, while the LSTM-based monitoring model successfully captured temporal dependencies in energy consumption patterns and achieved high prediction accuracy with robust generalization capability. Furthermore, the developed converter health assessment and fault detection mechanism enabled early identification of abnormal operating states and supported predictive maintenance strategies, thereby reducing potential downtime and improving system resilience. Communication performance analysis further verified the suitability of the proposed architecture for real-time deployment through low-latency and reliable data exchange mechanisms. Overall, the obtained results confirm that the proposed IoT-enabled monitoring framework provides a scalable, intelligent, and efficient solution for future smart grids, distributed energy systems, renewable-integrated networks, and advanced power electronic applications. Future research may extend this work by incorporating explainable artificial intelligence, digital twin technologies, federated learning, and adaptive edge computing for fully autonomous energy management systems.

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