

Multi source power monitoring and classification using IOT

Dr. D. Chitra¹, S Narmatha², V. Annapoorani³, Rumaniya P⁴

¹ Professor, Electronics and Communication Engineering, Mahendra Engineering College. Email: chitravalli2000@gmail.com

² Assistant Professor, Electronics and Communication Engineering, Knowledge Institute of Technology. Email: snece@kiot.ac.in

³ Assistant Professor, Electronics and Communication Engineering, Mahendra Institute of Technology.

Email: annapooraniv@mahendratech.org

⁴ Assistant Professor, Electronics and Communication Engineering, Sona College of Technology.

Email: rumaniya.ece163@gmail.com

Abstract: The rapid improvement of distributed energy classifications also smart electrical infrastructures requires effective monitoring and intelligent organization of several power sources. This paper suggests an progressive multi-source power monitoring also organization system exhausting Internet of Things (IoT) to improve energy management, dependability, and real-time decision-making. The suggested construction assimilates heterogeneous power sources for example grid supply, solar photovoltaic systems, battery storage, also backup generators concluded IoT-enabled sensing and communication segments. The classification workings smart sensors and embedded controllers to uninterruptedly measure electrical parameters together with voltage, current, power consumption, also frequency from every source. These information are transmitted to a cloud-based platform via IoT communication protocols for real-time monitoring and consideration. To be successful precise and intelligent organization, an IoT-based Particle Swarm Optimization optimized Deep Neural Network (IoT-PSO-DNN) model is recognized. In this method, Particle Swarm Optimization (PSO) is working to optimally tune the weights and hyper-parameters of the Deep Neural Network (DNN), thereby improving organization accurateness and convergence speediness. The suggested model proficiently recognizes also classifies dissimilar power sources, identifies anomalies, as well as optimizes energy utilization designs. The proposed technique increases classification effectiveness by permitting automated source transferring, fault detection, and load balancing. It similarly preservations predictive analytics for energy consumption besides improves scalability for smart grid presentations. Experimental outcomes establish that the classification accomplishes great classification accurateness, summary response time, and enhanced energy effectiveness associated to conventional machine learning-based monitoring classifications. This work delivers a scalable and intelligent solution for modern energy classifications, contributing to the improvement of smart homes, industrial automation, also sustainable energy management organizations. .

Keywords: Particle Swarm Optimization (PSO), Deep Neural Network (DNN), Internet of Things (IoT), ML Machine Learning, Energy Management,

1. INTRODUCTION

The collective demand for dependable and effective energy management has led to the rapid development of distributed energy organizations and smart electrical infrastructures. Current power classifications assimilate several heterogeneous energy sources for example grid supply, solar photovoltaic systems, battery storage units, also backup generators, creating monitoring as well as control more complex. Modern monitoring approaches are frequently incomplete in scalability, real-time receptiveness, besides intelligent decision-making abilities. To address these tasks, the integration of Internet of Things (IoT) technologies has developed as a promising resolution for real-time information acquisition and communication. IoT-enabled sensors then embedded systems facilitate endless monitoring of serious electrical parameters, containing voltage, current, power consumption, besides frequency. These information streams allow improved visibility and control over multi-source power atmospheres. Though, actual organization and investigation of such large-scale information necessitate progressive computational intelligence



methods. Conventional machine learning models frequently struggle through accurateness and adaptableness in dynamic atmospheres.

To overwhelmed these boundaries, deep learning methods, particularly Deep Neural Networks (DNNs), have expanded important consideration due to their capability to model complex nonlinear relations. Additionally, optimization methods for example Particle Swarm Optimization (PSO) can be working to improve the presentation of DNNs by tuning masses and hyper parameters effectively. In this context, this paper proposes an IoT-based PSO-optimized Deep Neural Network (IoT-PSO-DNN) framework for intelligent multi-source power monitoring and organization. The proposed organization permits precise identification of power sources, effective fault detection, and real-time decision-making. Furthermore, it maintenances automatic source switching, load balancing, and predictive energy analytics. The combination of IoT with enhanced deep learning improves classification effectiveness, decreases response time, as well as increases energy utilization. This work contributes to the progression of smart grids, smart homes, and industrial energy management classifications by provided that a scalable, reliable, also intelligent monitoring explanation.

2. LITERATURE SURVEY

[1] Charity M. Nkinyam (2025): This paper offerings the strategy and application of an sensible IoT-based monitoring organization for solar photovoltaic (PV) setting up, permitting real-time information acquisition on presentation parameters to increase conservation, effectiveness, also remote management in distributed energy presentations. [2] Mohamed Zarboubi (2025): This paper offerings a smart, low-cost monitoring classification that associations IoT sensors through a novel YOLO-Evo deep learning model to permit real-time pest detection and identification in apple orchards, sympathetic sustainable farming concluded precision-driven combined pest management methods. [3] Obaida AlHousrya (2026): This paper offerings an intelligent monitoring system that assimilates hybrid machine learning procedures with IoT substructure to recognize also predict driver fatigue in real-time controlled by involved electric vehicles, increasing road safety concluded adaptive warnings and vehicle-to-cloud communication for proactive interference. [4] Mr. Azamat Bakytbekov (2023): This paper offerings a novel energy harvesting classification that simultaneously detentions and associations ambient radio occurrence (RF) also thermal energy to power low-power IoT strategies, permitting sustainable, battery-free technique for environmental monitoring also smart substructure in remote or inaccessible locations. [5] Mohamed Elhoseny (2026): This paper provides a comprehensive evaluation of state-of-the-art IoT knowledge also computational samples for crop monitoring and precision irrigation, manufacturing recent enhancements while categorizing key tasks also upcoming exploration instructions to enhance water use effectiveness also agricultural sustainability.

[6] Maria Frontera-Bergasa (2025): This paper offerings an IoT-enabled multi-sensor platform planned to monitor serious environmental parameters—together with temperature, humidity, and light exposure—during medicine storage and transportation outdoor hospital settings, confirming pharmaceutical integrity and patient safety through real-time alerts and cloud-based data logging. [7] Ramesh Saha (2025): This paper presents SWAST KHOJ, a prototype IoT-based health monitoring system that qualifies real-time tracking of patient vital signs—such as heart rate and body temperature—concluded wearable sensors, facilitating remote healthcare delivery and initial alert generation for medical emergencies. [8] Arman Jahan Eva (2026): This paper presents the plan and performance evaluation of a hybrid solar-wind tree system combined with IoT-based real-time monitoring, exactly established for the climatic conditions of Bangladesh to optimize renewable energy generation and allow remote performance tracking for disseminated urban applications. [9] Florian Leischner (2026): This paper methodically associates the accuracy, reliability, and cost-effectiveness of low-cost single-parameter IoT sensors against traditional high-cost monitoring stations for stream water superiority assessment, evaluating their trade-offs to update scalable and accessible environmental monitoring resolutions. [10] Mohamed Elhoseny (2026): This paper comprehensively evaluations emerging IoT architectures, sensing technologies, and predictive models for crop monitoring and accuracy irrigation, synthesizing current advancements though classifying key challenges and upcoming research directions to improve water-use efficiency and supportable agricultural productivity.

[11] Antonio M. Albertia (2026): This paper establishes the application of NovaGenesis—a service-oriented, self-organizing, and programmable IoT architecture—for environmental monitoring using LoRa and Wi-Fi networks, allowing dynamic device orchestration, adaptive communication protocols, and flexible data management for scalable and resilient sensing positioning. [12] Anis ur Rehman (2024): This paper presents an innovative solar-powered multi-functional transportable charging device combined with IoT-based real-time monitoring, designed to improve energy access in remote and off-grid communities while allowing remote performance tracking, usage analytics, and effective energy management through cloud connectivity. [13] Rupali Atul Mahajan (2025): This paper suggests a novel framework that assimilates generative AI and transfer learning methods to improve personalization in IoT-based health monitoring systems, allowing adaptive model customization for specific patients while decreasing data requirements and improving predictive accuracy across diverse physiological patterns. [14] Mutiu Shola Bakare (2026): This paper presents the plan and implementation of an IoT-enabled inside environmental monitoring system that assimilates multi-parameter sensors through ESP32-WROOM microcontroller for real-time measurement of temperature, humidity, air quality, and other parameters, allowing remote data visualization and alert generation for smart building applications. [15] Mojgan Sami (2026): This paper presents a physics-informed machine learning method that leverages short-term IoT sensor data to accurately estimation building heat transferral coefficients in compliance with ASHRAE standards, allowing cost-effective thermal performance assessment and energy proficiency optimization without extended monitoring stages.

3. PROPOSED METHODOLOGY

The proposed methodology presents an intelligent multi-source power monitoring and classification framework based on Internet of Things (IoT) and a Particle Swarm Optimization optimized Deep Neural Network (IoT-PSO-DNN). Initially, multiple power sources such as grid supply, solar photovoltaic systems, battery storage, and backup generators are integrated into a unified monitoring system. IoT-enabled smart sensors and embedded controllers are deployed to continuously measure key electrical parameters including voltage, current, power, and frequency.

The composed information are pre-processed to remove noise, normalize values, and handle disappeared information for enhanced dependability. Consequently, the processed information are transferred to a cloud-based platform exhausting IoT communication protocols for real-time monitoring also storage. Feature extraction is accomplished to recognize important designs and appearances from the assimilated electrical signals.

These structures are then fed into a Deep Neural Network (DNN) for organization of dissimilar power sources besides detection of irregular environments. To improve the presentation of the DNN, Particle Swarm Optimization (PSO) is working to optimally tune network masses and hyperparameters, humanizing convergence speed and organization accurateness. The enhanced IoT-PSO-DNN model is qualified and established using real-time and historical information to confirm robustness and generalization ability. Based on the arrangement outcomes, the classification accomplishes intelligent decision-making for example automatic source switching, fault detection, and load balancing. Furthermore, predictive analytics are combined to forecast energy consumption designs also optimize energy consumption. The complete framework is considered to be scalable, effective, and suitable for smart grid and industrial presentations, confirming enhanced classification presentation, reduced response time, and improved energy management.

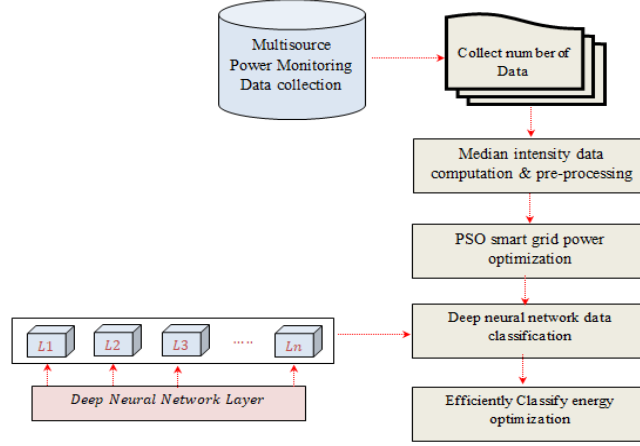


Figure 1. Architecture Diagram of Multi source power monitoring and classification using IOT

The cascade configuration increases borderline localization also decreases false alarms complete iterative contextual learning also feature development. The proposed methodology efficiently addresses noise, uncertainty, also complex impressive differences, creating it appropriate for real-time conservational monitoring and smart decision-support presentations.

A. IoT Partial Swarm Optimization data extraction

The proposed Particle Swarm Optimization (PSO) based IoT procedure is considered for multi-source power monitoring and intelligent classification in distributed energy environments. Firstly, heterogeneous IoT sensor nodes are deployed to bring together multi-domain parameters together with photovoltaic voltage, solar irradiance, wind speed, RF energy density, load current, battery state-of-charge, temperature, and environmental conditions. The sensed data are transmitted through low-power communication procedures such as LoRa or Wi-Fi to an edge gateway. A preprocessing phase is functional to remove noise, handle missing values, and normalize the dataset for uniform feature scaling. Feature vectors representative multi-source power characteristics are constructed for both IoT node. These features help as inputs to the optimization layer. A swarm of particles is initialized accidentally, where both particle signifies a candidate weight vector for feature selection and classification improvement. The initial velocity and position of both particle are allocated within predefined bounds. Personal best and global best positions are initialized based on fitness estimation. The fitness function is definite using classification error minimization across several energy states such as normal process, overload condition, low generation, and fault state

$$X_i = \{x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}\} \dots \text{Eq 3.1}$$

Where above equation $x(i)$ represents the feature vector of i th IOT node. N total number of feature, I sensor node index, j feature index

During both iteration, particle velocities are modernized using inertia, cognitive, and social modules to balance exploration and exploitation. Particle positions are then modernized to search for optimal feature weight groupings. The modernized particles are estimated using the defined fitness function based on classification accurateness. If a particle realizes enhanced performance than its previous best, the personal best is modernized accordingly. Likewise, the global best position is updated when higher classification performance is realized. This iterative optimization endures until convergence criteria such as supreme iteration count or lowest error threshold are fulfilled. The optimized feature weights are then functional to the IoT-based classification prototypical deployed at the edge layer

PSO- Normalization Computation

$$\text{Normalization} = \text{median}((ANW_{xy}(S))) \dots \text{Eq 3.2}$$

Where above equation represent the normalization represents the median feature extraction, $\text{median}(\cdot)$ denotes the median operator, and $\text{ANW}_{xy}(s)$ refers to the adaptive neighborhood window.

The Optimization feature is predicts the optimal power state using the optimized parameters. The system supports adaptive learning by periodically informing the swarm with anew composed IoT data. The suggested PSO-based IoT monitoring framework increases energy efficiency, increases decision-making accuracy, decreases computational complexity, and allows scalable deployment across solar PV systems, hybrid renewable plants, smart agriculture, health monitoring, and environmental surveillance systems. The procedure confirms dependable multi-source energy classification and maintainable IoT-driven monitoring in real-time distributed networks..

Partial velocity update min max extraction

$$\text{PSO-Z}_{\min} = \min(W_{xy}(S)) \quad \text{Eq 3.3}$$

$$\text{PSO-Z}_{\max} = \max(W_{xy}(S)) \quad \text{Eq 3.4}$$

Where $\text{PSO-Z}_{\min}$ represents the minimum pixel intensity in the window, $W_{xy}(s)$ denotes the adaptive neighbourhood window, $\text{PSO-Z}_{\max}$ represents the maximum pixel intensity in the window, and $W_{xy}(s)$ refers to the adaptive neighbourhood window.

PSO technique effectively extract feature monitoring data. The pre-processed image develops feature extraction performance. Feature extraction develops extra reliable after feature extraction. Classification accuracy is improved due to improved optimization technique. The procedure is computationally efficient. It is suitable for large-scale environmental monitoring. Adaptive window thus plays a significant role in power grid monitoring system.

B. Optimization: PSO-DNN Deep Convolutional Neural Network (CNN) Optimization:

The proposed Deep Neural Network (DNN) based IoT procedure is planned for intelligent multi-source power monitoring and classification in distributed energy systems. Firstly, heterogeneous IoT sensor nodes are positioned to obtain real-time electrical and environmental parameters together with photovoltaic voltage, solar irradiance, wind speed, RF harvested power, load current, battery state-of-charge, ambient temperature, and humidity. The sensed data are transmitted via low-power communication protocols such as LoRa, Wi-Fi, or NB-IoT to an edge gateway. A pre-processing phase is executed to remove noise, handle missing samples, and normalize the multi-source feature space. Both IoT node makes a structured feature vector representative energy production, storage, and consumption characteristics.

IOT Normalization

$$\text{DNN-N}(x,y) = \max(0, F_k(x,y)) \quad \text{Eq 3.5}$$

Where $\text{DNN-N}(x,y)$ represents the Convolutional neural network normalization feature map, $F_k(x,y)$ denotes the convolution output, and $\max(\cdot)$ represents the Rectified Linear Unit (ReLU).

The normalized dataset is separated into exercise and testing subsets. The deep neural network planning is modified with several hidden layers, nonlinear activation functions, and optimized weight matrices. Forward propagation calculates hierarchical feature representations from raw IoT information. The predicted power state probabilities are acquired from the output layer using a Softmax classifier. A cross-entropy loss function estimates classification performance across several energy states such as normal operation, overload, low generation, and fault condition.

During training, back propagation is functional to calculate gradients of the loss function with respect to network weights and biases. The parameters are iteratively modernized using gradient descent optimization to minimize classification error. Batch normalization and dropout mechanisms are optionally combined to increase generalization and decrease overfitting. The training procedure carry on until convergence criteria such as lowest

validation loss or maximum epoch threshold are fulfilled. The optimized DNN model is deployed at the IoT edge layer for real-time power state monitoring and predictive analytics. The system constantly obtains streaming IoT data and executes inference to classify energy conditions. Adaptive retraining is maintained by periodically informing the model with anew acquired sensor data.

Feature Map energy optimization

$$\text{Energy Optimization(EO)} = \text{Vector (Pk)} \dots \text{Eq 3.6}$$

Where EO represent Energy optimization Pk represents the pooled feature maps, f denotes the one-dimensional feature vector, and Vector represents the map feature vectorization operation.

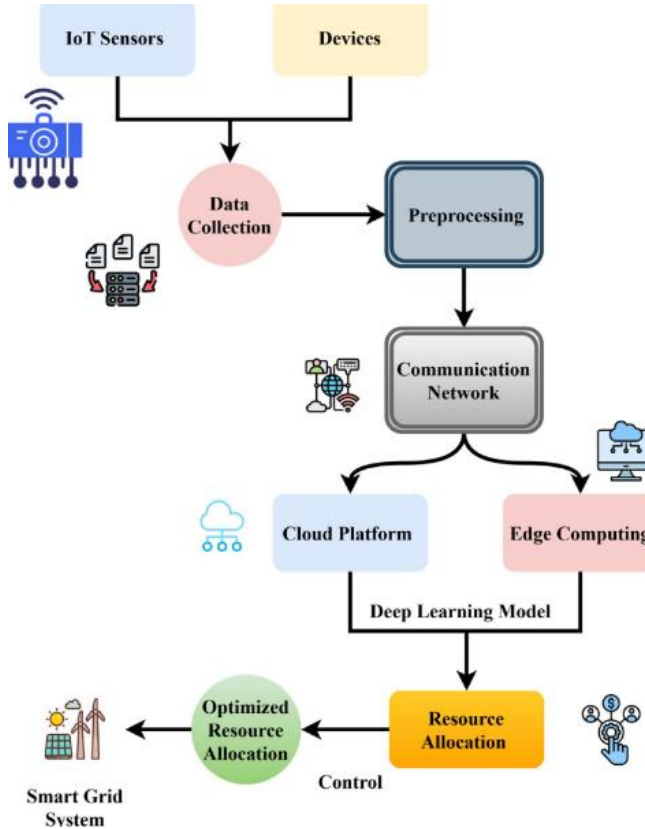
The extract feature maps are flattened into feature vectors. These vectors characterize spatial and semantic data of the image. The texture Deep-CNN automatically learns discriminative features without manual design. Feature extraction is optimized through back propagation. The learned features adapt to varying pollution intensities.

IOT Connected Layer Transformation

$$\text{Layer Optimization} = \text{WfCL T} + \text{bf} \dots \text{Eq 3.7}$$

Where WfCL represents the weight matrix of the fully connected layer, bf denotes the bias vector, T represents the Layer transformation vector, and z denotes the extracted high-level features.

The suggested DNN-driven IoT framework increases monitoring accuracy, increases fault detection capability, and allows intelligent energy management across solar PV systems, hybrid renewable plants, smart agriculture, environmental monitoring platforms, and health-oriented IoT infrastructures. The architecture confirms scalability, computational effectiveness, and robust multi-source energy classification in dispersed IoT ecosystems.



C. Classification: IOT-PSO- DNN Smart Grid real time Monitoring Classification

The suggested Smart Grid IoT-based real-time monitoring algorithm is planned for multi-source power monitoring and intelligent classification within distributed smart energy substructures. Firstly, heterogeneous IoT sensor nodes are positioned across photovoltaic systems, wind turbines, battery storage units, RF energy harvesters, smart meters, and load terminals within the smart grid. These nodes constantly measure voltage, current, power factor, frequency, irradiance, temperature, battery state-of-charge, and load demand parameters.

The sensed multi-source data are transmitted via secure statement procedures such as LoRaWAN, Wi-Fi, or NB-IoT to an edge-enabled smart grid gateway. A pre-processing layer achieves signal conditioning, noise filtering, time synchronization, and normalization to confirm consistent information representation. The treated measurements are structured into feature vectors representative generation, storage, and consumption characteristics in real time. The dataset is deposited in an edge-cloud design for continuous analytics.

$$EC(X,Y) = EC_{out}/EC_{in}(x,y).....Eq\ 3.8$$

Where x,y represents the energy efficiency condition, $(\cdot)$ denotes the cascade DNN, and EC represents the energy extracted deep feature classification x,y represent classify feature.

A real-time monitoring engine estimates system stability and power balance conditions. Feature extraction methods classify serious indicators such as load variation, generation fluctuation, and voltage deviation. A classification model is assimilated to classify smart grid states into usual operation, overload condition, distributed fault, low generation, and energy surplus scenarios.

$$Classification = \operatorname{argmax} (Y_k(x,y))..Eq\ 3.5$$

Where argmax represents the Maximum argument operator, Y_k Predicted probability of state kk , and x,y represent classify feature, k represents total number of grid condition extracted deep feature classification.

The classification model is proficient using labeled historical IoT data. Through inference, the model calculates probability scores for both energy states using the incoming real-time feature vector. The procedure continuously relates expected states with predefined safety thresholds to detect anomalies. If unbalanced atmospheres are recognized, automatic control signals are activated to optimize load distribution otherwise activate backup energy resources.

The procedure supplementary maintenances adaptive learning by periodically reeducation the organization model through anew collected IoT information to continue prediction accurateness further down dynamic grid environments. Real-time imagining consoles provide monitoring understandings for technicians. The proposed IoT-based smart grid monitoring framework upsurges energy effectiveness, increases reliability, decreases outage possibilities, also permits sustainable management of multi-source renewable also conventional power classifications in distributed smart grid atmospheres.

4. Experimental Evaluation

The investigational estimation of the suggested IoT-PSO-DNN classification is accompanied using real-time and replicated information together from several heterogeneous power sources, together with grid supply, solar photovoltaic classifications, battery storage, also stoppage generators. IoT-enabled smart sensors and embedded supervisors are organized to amount electrical parameters for example voltage, current, power consumption, as well as frequency at regular intervals. The information acquisition procedure is carried out unceasingly to imprisonment dynamic differences below dissimilar functioning environments, together with usual operation, peak load, also responsibility scenarios.

Composed information are transferred to a cloud-based platform concluded usual IoT communication protocols for centralized storing and processing. To confirm information superiority, preprocessing methods for example noise

filtering, normalization, besides outlier removal are functional. The dataset is then characterized based on the type of power source also classification complaint to maintenance supervised learning.

A sufficient volume of information examples is composed to safeguard model dependability and simplification. The dataset is distributed into exercise and testing sets to appraise the presentation of the suggested IoT-PSO-DNN model. Presentation metrics for example organization accurateness, Energy Efficiency, Time Consumption, also response time are used for estimation. Comparative analysis is similarly implemented against conventional machine learning models to authenticate the efficiency of the proposed method. The experimental operation establishes enhanced accuracy, faster convergence, and enhanced energy effectiveness below several real-time functioning environments.

Dataset Description

The input dataset contains of replicated real-time electrical power monitoring information composed from several distributed energy sources, together with grid supply, solar photovoltaic (PV), battery storage, besides backup generators. IoT-enabled sensors also smart meters are supposed to uninterruptedly amount electrical parameters for example voltage, current, power consumption, frequency, also temperature. The dataset integrates dissimilar functioning environments, together with usual procedure, overload, peak-demand environments, also fault environments, to estimate the organization ability of the proposed IoT-PSO-DNN model.

The experimental dataset involves 10,000 replicated real-time power observing patterns demonstrative several distributed energy sources, comprising grid supply, solar photovoltaic organizations, battery storage, besides backup generators. Every example comprises eight electrical also conservational parameters, namely voltage, current, power consumption, frequency, high temperature, solar power generation, battery state-of-charge (SOC), as well as load demand. The generated samples represent different operating conditions, including normal operation, high-load conditions, overload conditions, and electrical fault conditions.

Dataset Name :

IoT-Enabled Smart Grid Dataset – Kaggle

The dataset is pre-processed using data cleaning, noise filtering, and normalization techniques before being provided to the PSO optimization module. The dataset is divided into 80% training (8,000 samples) and 20% testing (2,000 samples). The optimized features and DNN parameters are subsequently used for multi-class classification of the power-system operating conditions.

Attribute	Description
Dataset Type	Simulated real-time IoT power monitoring dataset
Application Domain	Smart Grid / IoT / Energy Management
Data Source	Grid, Solar PV, Battery Storage, Backup Generator
Total Samples	10,000
Input Features	8
Features	Voltage, Current, Power Consumption, Frequency, Temperature, Solar Power, Battery State-of-Charge, Load Demand
Classification Type	Multi-class classification
Number of Classes	4
Classes	Normal, High Load, Overload, Fault
Data Format	Numerical sensor measurements

Data Acquisition	Continuous/simulated IoT sensing
Pre-processing	Data cleaning, noise filtering, normalization
Optimization	Particle Swarm Optimization (PSO)
Classifier	Deep Neural Network (DNN)
Training : Testing	80% : 20%
Training Samples	8,000
Testing Samples	2,000

5. Result and Discussion

A. Classification Accuracy

Accuracy is defined as the proportion of the correct predictions (both total no of data and classified correct data) presented by the detection system out of every prediction. Accuracy is mathematically calculated below following equation,

$$\text{Classification Accuracy (\%)} = \text{No Of Correctly Classified} / \text{Total No of Data} * 100 \dots \text{Equ 5.1}$$

Proposed technique (PSO-DNN) higher accuracy when compared with Existing 1 SCADA[1] and Existing 2 YOLO-Evo[2] technique

Table I Prediction Accuracy of IOT PSO-DNN

Number of Input Data	Classification Accuracy (%)		
	PSO-DNN	SCADA	YOLO-Evo
1000	97	91	88
2000	95	92	84
3000	97	94	81
4000	94	90	84
5000	95	93	85
6000	96	92	83
7000	94	91	89
8000	96	93	87
9000	97	95	89
10000	95	92	90

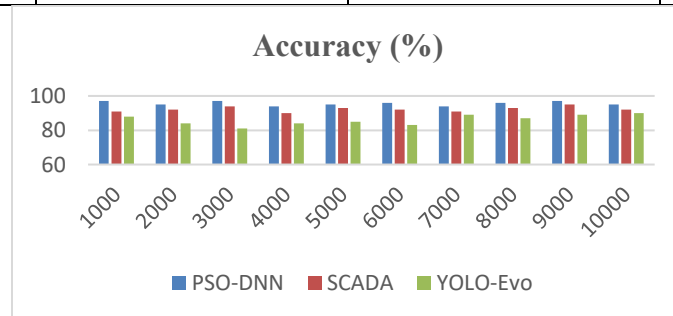


Figure 2 . Classification Accuracy(%) Comparison

B. Energy Efficiency (%)

Error rate is defined as the ratio of incorrect predictions made by the model out of the total number of cases,

$$\text{Energy Efficiency} = (\text{Eout}/\text{Ein}) * 100 \dots \text{Equ 5.2}$$

Where above equation 5.2 represent Eout and Ein –Energy Out and Energy In,

Table II Energy efficiency of IOT PSO-DNN

Number of Input Data	Energy Efficiency (%)		
	PSO-DNN	SCADA	YOLO-Evo
1000	7	12	14
2000	9	16	19
3000	8	18	22
4000	11	17	21
5000	10	18	22
6000	9	19	23
7000	6	15	20
8000	9	18	21
9000	7	13	17
10000	8	12	18

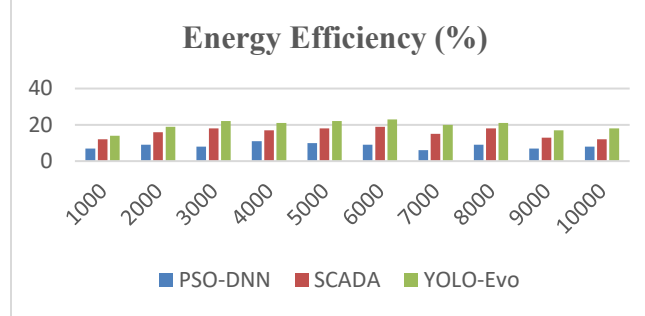


Figure 3 . Energy Efficiency (%) Comparison

model outperforms Proposed technique (PSO-DNN) higher accuracy when compared with Existing 1 SCADA[1] and Existing 2 YOLO-Evo[2] technique technique in terms of prediction accuracy and error rate. This leads into greater dependability and more accurate decision-making in website phishing detection, eventually surpassing the performance of previously used strategies.

C. Time Consumption (ms)

Time Consumption is determined as the number of time taken by the system to process the task from input to output. Additionally, it analyses the input and produce the prediction

$$\text{TC} = \text{Time at End of Consumption} - \text{Time at Start of Consumption} \dots \text{Equ5.3}$$

Table III Time Consumption of IOT PSO-DNN

Number of Input Data	Time Consumption (ms)
----------------------	-----------------------

	PSO-DNN	SCADA	YOLO-Evo
1000	31	38	56
2000	29	35	51
3000	41	51	59
4000	48	54	64
5000	51	59	66
6000	54	67	70
7000	56	71	76
8000	62	79	83
9000	65	81	87
10000	66	85	90

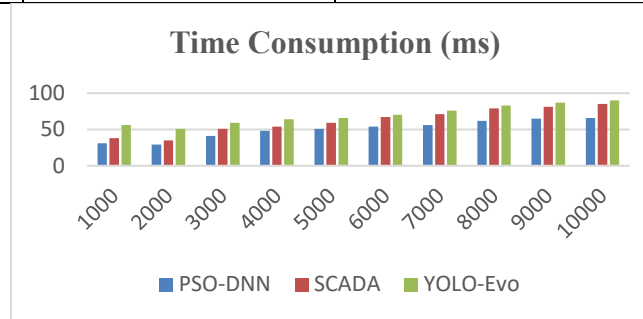


Figure 4 . Prediction Time(ms) Comparison

Produces faster computation and prediction processes. Compared to previous techniques, the RCNN built with this improved knowledge set completes the arrangement substantially faster, hence removing the absolute prediction time. The suggested technique Proposed technique (PSO-DNN) higher accuracy when compared with Existing 1 SCADA[1] and Existing 2 YOLO-Evo[2] technique.

6. CONCLUSION

The proposed IoT-based PSO-optimized Deep Neural Network (IoT-PSO-DNN) framework provides an effective solution for intelligent multi-source power monitoring and classification. The mixture of IoT technology permits real-time information attainment also seamless communication through diverse energy sources. By integrating Particle Swarm Optimization, the Deep Neural Network realizes improved accurateness, faster convergence, also optimal parameter tuning. The classification efficiently categorizes dissimilar power sources for example grid, solar, battery, and generators with high precision. Furthermore, the proposed method increases organization reliability complete effective fault detection and automated source switching machineries. It also maintenances dynamic load balancing, confirming optimal utilization of available energy resources. The occurrence of predictive analytics permits improved forecasting of energy consumption designs. Experimental outcomes establish superior presentation in relationships of classification accurateness, reduced response time, and enhanced energy effectiveness associated to conventional methods. The scalability of the framework creates it appropriate for distribution in smart grids, industrial systems, also smart home applications. Overall, the proposed system contributes to sustainable energy management by decreasing energy wastage and refining operational efficiency. Future work can focus on integrating advanced optimization techniques and expanding the system for large-scale real-world implementations.

REFERENCES

1. Charity M. Nkinyam, Peter A. Olubambi, Chika Oliver Ujah, "Development of a low-cost monitoring device for solar electric (PV) system using internet of things (IoT)", Received 19 February 2025, Received in revised form 18 July 2025, Accepted 15 September 2025, Available online 16 September 2025, <https://doi.org/10.1016/j.rineng.2025.107324>.
2. Mohamed Zarboubi, Abdelaziz Bellout, Samira Chabaa, "Enhancing integrated pest management with IoT and YOLO-Evo: A smart, low-cost monitoring system for sustainable apple farming", Received 25 July 2025, Received in revised form 24 September 2025, Accepted 21 December 2025, Available online 25 December 2025, <https://doi.org/10.1016/j.rineng.2025.108850>.
3. Obaida AlHousrya, Aseel Bennagi, Petru A. Cotfas, "A hybrid machine learning and IoT system for driver fatigue monitoring in connected electric vehicles", Received 13 November 2025, Received in revised form 26 December 2025, Accepted 14 January 2026, Available online 18 January 2026, <https://doi.org/10.1016/j.mlwa.2026.100845>.
4. Mr. Azamat Bakytbekov, Thang Q. Nguyen, Michael S. Strano, "Synergistic multi-source ambient RF and thermal energy harvester for green IoT applications", Received 23 October 2022, Received in revised form 27 December 2022, Accepted 4 January 2023, Available online 9 January 2023, <https://doi.org/10.1016/j.egy.2023.01.027>.
5. Mohamed Elhoseny, Khadija Jahid, Rachid Latif, "Recent advances in IoT-driven crop monitoring and precision irrigation: Technologies, models, and future challenges", Received 20 August 2025, Received in revised form 3 January 2026, Accepted 28 January 2026, Available online 4 February 2026, <https://doi.org/10.1016/j.sciaf.2026.e03222>.
6. Maria Frontera-Bergasa, Miguel Vinaixa-Fernández, Bartomeu Oliver-Riera, "A Multi-Sensor IoT Platform for monitoring medicine storage beyond the hospital", Received 24 March 2025, Received in revised form 19 June 2025, Accepted 18 July 2025, Available online 29 July 2025.
7. Ramesh Sahaa, Sanjeev Kumar Bharadwajb, Sohail Saif, "SWAST KHOJ: An IoT-driven real-time health monitoring system prototype", Received 16 October 2024, Received in revised form 29 July 2025, Accepted 7 October 2025, Available online 13 October 2025, <https://doi.org/10.1016/j.iot.2025.101796>.
8. Arman Jahan Eva, Al Amin, Md Nasir Uddin, Tamim Ahmed, "Design and Performance Analysis of a Hybrid Solar-Wind Tree System with IoT based Real-Time Monitoring in Bangladesh", Received 3 June 2025, Received in revised form 16 October 2025, Accepted 13 January 2026, Available online 27 January 2026, <https://doi.org/10.1016/j.ecmx.2026.101566>.
9. Florian Leischner, Thorsten Mietzel, Nadine Gerner, "A comparison between low-cost single-parameter IoT sensors and traditional high-cost monitoring stations for stream water quality assessment", Received 16 September 2025, Received in revised form 6 January 2026, Accepted 25 January 2026, Available online 31 January 2026, <https://doi.org/10.1016/j.eti.2026.104788>.
10. Mohamed Elhoseny, Khadija Jahid, Rachid Latif, "Recent advances in IoT-driven crop monitoring and precision irrigation: Technologies, models, and future challenges", Received 20 August 2025, Received in revised form 3 January 2026, Accepted 28 January 2026, Available online 4 February 2026, <https://doi.org/10.1016/j.sciaf.2026.e03222>.
11. Antonio M. Albertia, Epper Bonomob, Rodrigo H. Santos, "Applying NovaGenesis: A service-oriented, self-organizing, and programmable IoT architecture for LoRa and Wi-Fi-based environmental monitoring", Received 28 November 2024, Received in revised form 7 January 2026, Accepted 8 January 2026, Available online 10 January 2026, <https://doi.org/10.1016/j.comcom.2026.108423>.
12. Anis ur Rehman, Ishaq G. Muhammad Alblushi, Muhammad Fahad Zia, "A solar-powered multi-functional portable charging device (SPMFPCD) with internet-of-things (IoT)-based real-time monitoring—An innovative scheme towards energy access and management", Received 8 March 2024, Received in revised form 11 August 2024, Accepted 4 September 2024, Available online 12 September 2024, <https://doi.org/10.1016/j.grets.2024.100134>.
13. Rupali Atul Mahajan, Rajesh Dey, Muhammad Mansoor Alam, "Enhancing personalization in IoT-based health monitoring via generative AI and transfer learning", Received 12 January 2025, Received in revised form 13 August 2025, Accepted 15 September 2025, Available online 20 September 2025, <https://doi.org/10.1016/j.eij.2025.100788>.
14. Mutiu Shola Bakare, Kazibwe Abubaker, "IoT-based indoor environmental monitoring system using multi-parameter sensing and ESP32-WROOM integration", Received 10 November 2025, Accepted 12 January 2026, Available online 22 January 2026, <https://doi.org/10.1007/s44291-026-00157-3>.
15. Mojgan Sami, Francisco Sierra, "Physics-informed machine learning for ASHRAE-compliant heat transfer coefficient estimation from short-term IoT monitoring", Received 14 October 2025, Received in revised form 8 December 2025, Accepted 7 January 2026, Available online 13 January 2026, <https://doi.org/10.1016/j.enbuild.2026.116984>.