Performance and Analysis of Soft Computing Techniques with Energy Management Framework in IoT Networks

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Abstract: An EV (ELECTRIC VEHICLE) charging system based on machine learning (ML) has the capacity to generate precise future judgements based on previous data. A number of ML algorithms, including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbours (KNN), are contrasted in terms of their performances in optimisation. The outcomes verify the reliability of the use of KNN for the management of EVs to ensure high accuracy. The KNN model successfully minimizes power losses and voltage fluctuations and achieves peak shaving by flattening the load curve. Novel Sequence Learning-Based Energy Forecasting framework includes a unique mechanism for predicting future energy consumption. It uses sequence learning techniques, which are often employed in machine learning and artificial intelligence for tasks involving time series data. The goal is to forecast energy consumption efficiently and with low error rates. The cloud server and smart grids work together to manage energy demand and response effectively. These techniques used to clean, transform, and prepare the data for analysis. The framework incorporates energy decision-making algorithm specifically designed for an efficient forecasting. Short-term forecasting is essential for managing energy demand and response in real-time. It appears that this framework combines various technologies and methodologies to create a comprehensive system for real-time energy management in an IoT environment. The focus is on efficient and accurate energy forecasting and decision-making to optimize energy consumption.

1 Introduction

Internet of Things (IoT)-enabled Wireless Sensor Networks (WSNs) are increasingly finding applications in various domains, including healthcare [1], consumer electronics [2], and even image transmission [3]. However, the growing interconnectivity among these networks, their widespread deployment, and the inherently open nature of their communication channels expose them to a range of security threats, potentially leading to network casualties [4]. In recent times, intrusion detection systems have undergone a transformative shift with the integration of artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), into both offensive and defensive strategies for IP-enabled wireless networks. These AI-based algorithms offer adaptive defence mechanisms against security threats, aiming to prevent and minimize the impacts or casualties they might cause. Researchers have applied machine learning and deep learning models to tasks such as intrusion detection [5], malware detection [6], cyber-physical attacks [7], and data privacy protection [8]. Among machine learning models, neural networks, with their self-learning capability, effective classification, and scalability, have attracted significant attention. Neural networks have proved promising for intrusion detection, with Extreme Learning Machines (ELM) gaining popularity as single feedforward neural networks (SLFNN) designed to efficiently detect various attacks in wireless networks [9]. Additionally, Wenjie et al. [10] introduced Kernelized Extreme Learning Machine (KELM), a methodology that overcomes the limitations of traditional extreme learning machines, offering improved results in terms of time and accuracy. It's worth noting that these algorithms have demonstrated effectiveness but may face challenges in detecting diverse attack categories and real-time testing. The growing diversity of attacks can lead to complex data patterns, potentially resulting in misclassifications. To address these challenges, many deep learning models, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have been proposed for intrusion detection systems. These deep learning models offer improved accuracy in detection and help reduce false alarm rates. Notably, researchers have explored high-performance deep learning algorithms like Channel Boosted Residual Convolutional Neural Networks (CBR-CNN) [12] to further enhance the capabilities of intrusion detection systems.

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2 Microgrid with IoT for energy management and control

Fig. 1 illustrates the Flow diagram of Microgrid with IoT for energy management and control. In this setup, a 3 kW renewable energy source feeds power into a 24 V DC bus via a buck-boost Maximum Power Point Tracking (MPPT) converter. The IoT-based module serves as the vital link between the energy source, loads, and the battery energy storage system. Additionally, it facilitates communication with nearby microgrids, enabling power exchange during periods of low or high demand. The IoT device plays a crucial role in collecting data from both the energy source and the loads. The Deep Neural Network (DNN) utilized in our system comprises multiple processing layers capable of extracting hierarchical features from the input data. This DNN operates by emulating the functioning of the human brain, allowing it to model complex patterns in the data effectively. In our experimental results, we achieved high accuracy when training artificial intelligence (AI) using the dataset we generated. This underscores the potential of deep learning in analyzing user behaviours, including events and applications, in intricate IoT systems. Furthermore, deep learning holds promise for enabling IoT devices to learn and adapt to complex behavioural patterns more effectively than traditional learning techniques.

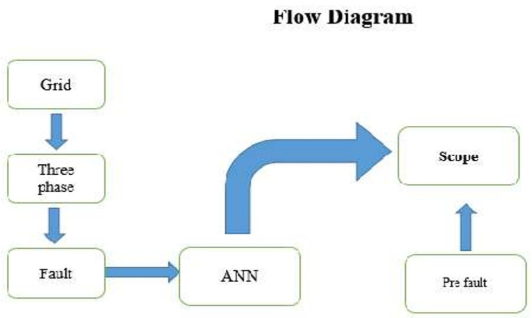


Fig.1. Flow diagram of Microgrid with IoT for energy management and control

3 Modelling and Analysis of IoT

Using Soft computing Learning

Technical learning is often regarded as the cornerstone of contemporary artificial intelligence. It has found extensive applications in fields like computer vision, speech recognition, robotics, and many other domains. In comparison to traditional machine learning techniques, deep learning offers several key.

Deep learning neural networks incorporate numerous hidden layers. This architecture enables DL to model and capture intricate, nonlinear relationships between attributes. Popular neural network architectures, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, possess the ability to directly extract and identify valuable features from raw data. This is in contrast to traditional machine learning, which often relies on manually crafted statistical features.

The utilization of deep neural networks in deep learning empowers AI systems to handle more complex and unstructured data, paving the way for advancements in various applications. Fig. 2 shows the block diagram of system architecture.

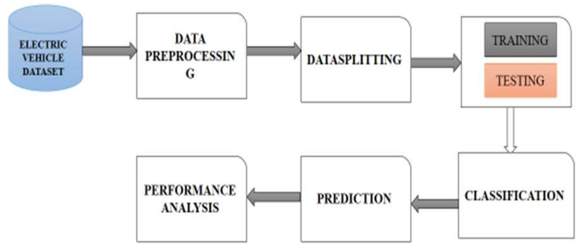


Fig.2. Block diagram of System Architecture

4 AI Based Automatic Detection in Transmission Fault Modeling and Dataset Generation

This structure provides a framework for presenting your research on fault protection management using the CatBoost algorithm for voltage and current data classification. The data originates from a simulated faulty transmission line model, which we designed using Matlab/Simulink and represents a 330 kV, 500 km-long transmission line. From this model, we extracted a dataset of 93, 340 fault records. Our approach involved utilizes the CatBoost classifier to categorize the faults, after we trained the data using different machine learning algorithms with various parameters. Remarkably, the CatBoost algorithm achieved the highest accuracy, reaching 99.54%, with a minimal error rate of 0.46% after 748 iterations out of 1000. We selected this algorithm due to its exceptional performance in fault classification, considering metrics such as accuracy, precision, and speed. Furthermore, CatBoost stands out for its user-friendliness and its ability to handle multiple datasets effectively. In comparison, both the support vector machine and artificial neural network methods exhibited lengthier training times, taking significantly more time, 58.5 seconds in this case. Proper fault classification techniques, as exemplified by the CatBoost algorithm, play a pivotal role in efficient fault management, contributing to the overall reliability of power systems.

4 Detection and classification of transmission line faults

Accurate detection and classification of transmission line (TL) faults play a crucial role in identifying the root causes of faults and ensuring the rapid restoration of power networks. Deep learning has emerged as a transformative technology capable of automatically extracting representative features from vast datasets, offering a significant breakthrough in fault analysis. However, existing deep learning-based fault diagnosis models often require extensive data covering various fault conditions to generalize effectively. In the TL domain, defining and collecting incepted fault features for all possible scenarios can be challenging. In response to these challenges, our paper introduces an unsupervised framework for fault detection and classification (FDC) in TL using a capsule network (CN). However, instead of relying on the baseline CN, we have extended it with a sparse filtering technique. This extended model, known as the capsule network with sparse filtering (CNSF), autonomously learns valuable fault features, enhancing model performance without the need for extensive data. Our proposed scheme takes 1/2 cycle post-fault three-phase signals and encodes them into a single image, serving as input for the CNSF model. We have assessed the effectiveness of the CNSF model across four different TL topologies, demonstrating its adaptability to topology changes resulting from control actions or cascading faults. Additionally, we've evaluated the model's performance under noise, high impedance faults (HIF), and varying line parameters, affirming its high reliability. Furthermore, we've conducted a comprehensive comparative study to establish the state-of-the-art performance of the proposed model**.** Fig. 3 shows the block diagram for the detection and classification of transmission line faults.

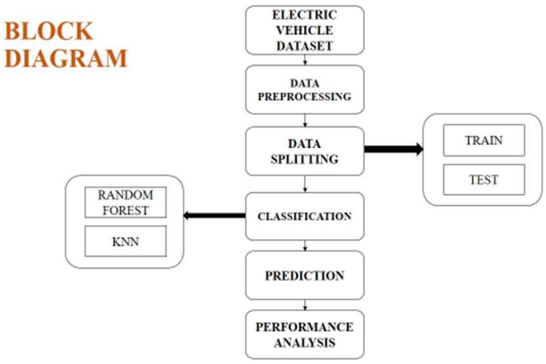


Fig. 3. Detection and classification of transmission line faults

6 Proposed Work

Simulation diagram of three phase service fault network

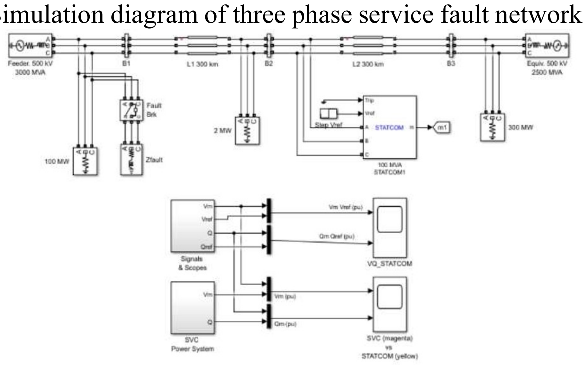


Fig. 4. Simulation diagram of proposed system

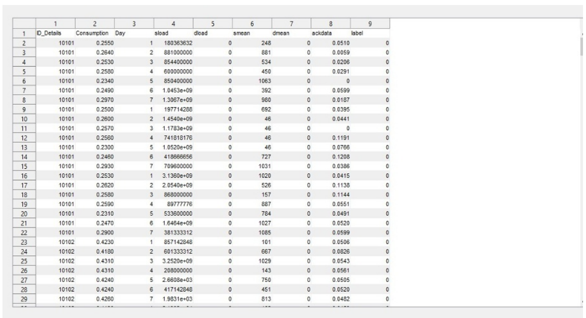
Fig. 4 shows the simulation diagram of the proposed system. Also, Table 1 shows the system description with the necessary parameters.

System Description

Sampling	16700 Hz
Amount Of Sampling In 1 Signal	334 Sampling
Voltage Signal	3 Phase
Current Signal	3 Phase
Type Of Fault	11 types

7 Simulation Result

To evaluate the effectiveness of our proposed system, we conducted simulations using soft computing techniques learning with intelligent energy management framework in IoT networks. These simulations aimed to assess the system's performance under various system disturbances. We have presented the simulation findings based on datasets. In these simulations, we utilized three-phase voltage and current signals generated from our power system model to train AI for automatic fault detection. Simulations served as a means to generate training and validation datasets. Data validation was performed to evaluate the accuracy and performance of the AI method. Looking ahead, future implementations of this method may involve utilizing real data collected by various devices deployed within the power system. This transition to real-world data holds significant promise for enhancing the practical applicability of the system. It's worth noting that our approach is based on the Convolutional Neural Network (CNN) algorithm



	1	2	3	4	5	6	7	8	9
1	ID_Details	Consumption	Day	sload	dload	smean	dmean	ackdata	label
2	10101	0.2550	1	180363632	0	248	0	0.0510	0
3	10101	0.2640	2	881000000	0	881	0	0.0059	0
4	10101	0.2530	3	854400000	0	534	0	0.0206	0
5	10101	0.2580	4	600000000	0	450	0	0.0291	0
6	10101	0.2340	5	850400000	0	1063	0	0	0
7	10101	0.2490	6	1.0453e+09	0	392	0	0.0599	0
8	10101	0.2970	7	1.3067e+09	0	980	0	0.0187	0
9	10101	0.2500	1	197714288	0	692	0	0.0395	0
10	10101	0.2600	2	1.4540e+09	0	46	0	0.0441	0
11	10101	0.2570	3	1.1783e+09	0	46	0	0	0
12	10101	0.2560	4	741818176	0	46	0	0.1191	0
13	10101	0.2300	5	1.0520e+09	0	46	0	0.0766	0
14	10101	0.2460	6	418666656	0	727	0	0.1208	0
15	10101	0.2930	7	709600000	0	1031	0	0.0386	0
16	10101	0.2530	1	3.1360e+09	0	1020	0	0.0415	0
17	10101	0.2620	2	2.0540e+09	0	526	0	0.1138	0
18	10101	0.2580	3	868000000	0	157	0	0.1144	0
19	10101	0.2590	4	89777776	0	887	0	0.0551	0
20	10101	0.2310	5	533600000	0	784	0	0.0491	0
21	10101	0.2470	6	1.6464e+09	0	1027	0	0.0520	0
22	10101	0.2900	7	381333312	0	1085	0	0.0599	0
23	10102	0.4230	1	857142848	0	101	0	0.0506	0
24	10102	0.4180	2	601333312	0	667	0	0.0826	0
25	10102	0.4310	3	3.2520e+09	0	1029	0	0.0543	0
26	10102	0.4310	4	208000000	0	143	0	0.0561	0
27	10102	0.4240	5	2.6608e+03	0	750	0	0.0505	0
28	10102	0.4240	6	417142848	0	451	0	0.0520	0
29	10102	0.4260	7	1.9831e+03	0	813	0	0.0482	0

Fig.5. Data loading

This detailed investigation and proposed framework aim to leverage the capabilities of controllable IoT devices for energy load forecasting, ensuring practicality and efficiency in real-world applications within smart homes and industries. By integrating a multi-layered GRU network into the proposed framework, to aim to enhance the accuracy of short-term load forecasting, providing a more sophisticated and efficient solution for energy management. These dependable, resource-constrained devices with cloud-based communication into the framework, to enhance the overall robustness and scalability of the system. This approach allows for efficient energy load forecasting while ensuring reliable communication with the smart grid for improved energy management as in

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communication channel. The energy management framework becomes more accessible and applicable in diverse scenarios, providing tangible benefits to users in smart homes and industries. Incorporating sequential learning with fuzzy logic and exploring efficient set theory concepts integrated with CNNs using weighted fusion schemes, your framework gains a more sophisticated ability to adapt to real-time changes and uncertainties in energy consumption patterns, making it highly robust and effective.

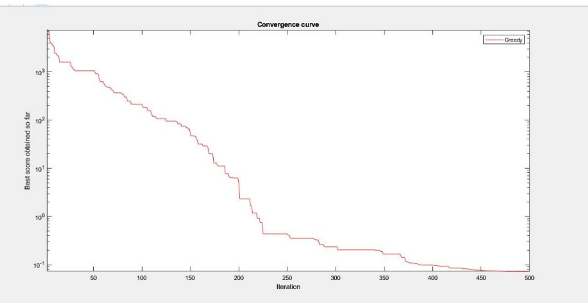

Fig. 6. Convergence curve

In Figures 6 and 7, we present residual curves where the x-axis represents the predicted response, and the y-axis represents the residual error. The proximity of the residual error to the predicted observation is indicative of the candidate algorithm's effectiveness. This inference aligns with both empirical and absolute values, as illustrated.

In the course of our investigation, we identified the top three performing machine learning algorithms for predicting energy demand at a university campus based on our datasets. Subsequently, we conducted an in-depth examination of various performance parameters to comprehensively evaluate the algorithms.

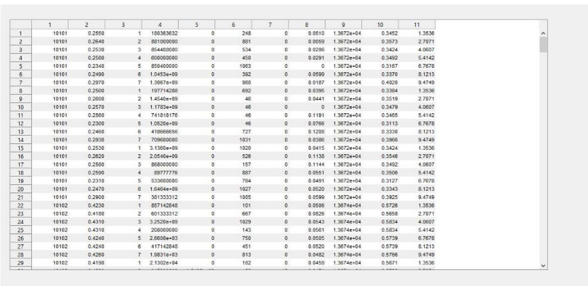

Fig. 7. Epoch's iteration (500) error of proposed system

Figures 6 and 7 display the prediction versus actual and residual plots for each evaluated algorithm. We assessed the performance of 24 machine learning prediction algorithms based on benchmark parameters. In the prediction versus actual graph, the x-axis represents the true response, while the y-axis depicts the predicted response. The degree of linearity in these curves is highlighted in black, while the actual observations are marked as blue dots. This graph allows us to visually assess the perceptual variance by observing the distance between the predicted and actual values

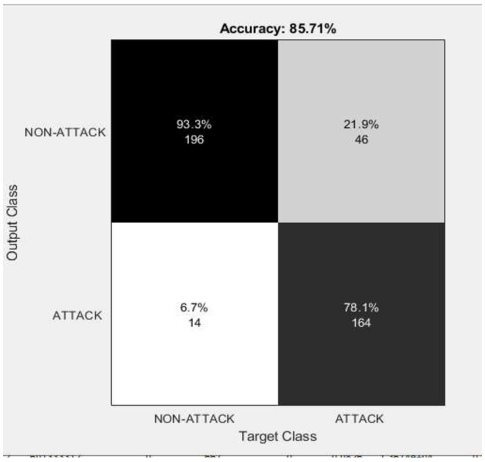

Fig. 8. Label encoding (attack & non attack) of Proposed system

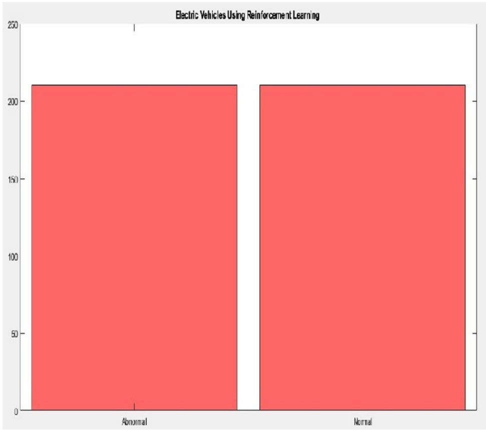

Fig. 9. Feature extracted confusion metrics of proposed system

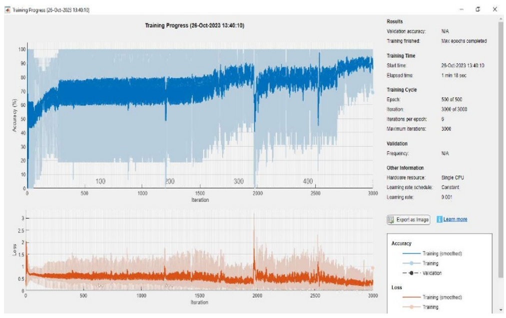

Fig. 10. Graph of CNN algorithm accuracy 10x

Traditional neural networks are designed to process a single input at a time. In contrast, Recurrent Neural Networks (RNNs) are capable of handling inputs across multiple time steps and analyzing patterns in a series. RNNs receive input and produce output at each time step, making them well-suited for sequential data analysis. However, RNNs often encounter a challenge known as the "vanishing gradient problem." This problem arises when the network forgets the influence of earlier time steps in a lengthy sequence, resulting in the loss.

Balancing the distribution of processing tasks between edge, fog, and cloud computing layers, efficiently handle long sequences of raw energy data while meeting the real-time constraints of energy forecasting applications. Significant information from the initial time steps may be lost due to the vanishing gradient problem. To address this issue, Long Short-Term Memory (LSTM) networks come into play. LSTMs incorporate specialized gates, including input gates, forget gates, and output gates, which enable them to effectively capture and learn long-term sequential information. These gates play a crucial role in mitigating the vanishing gradient problem, ensuring that important information from earlier time steps is retained and utilized.

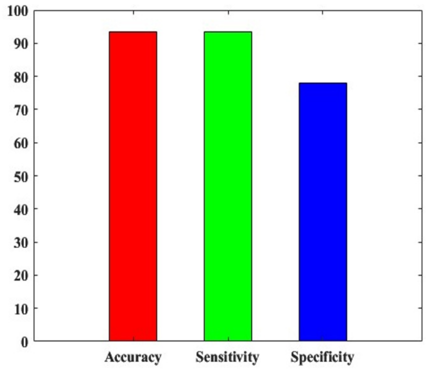

Fig.11. Bar graph for Performance analysis

Tabulation for Performance analysis

	Accuracy	Sensitivity	Specificity
%	93.3333	93.3333	78.0952

8 Conclusion

Three-phase voltage and current signals from your power system model simulation to train an AI model for automatic fault detection, enhancing the resilience and reliability of the power system. Simulation is a pivotal step in generating both training and validation datasets. Data validation plays a critical role in assessing the accuracy and performance of the AI method. For future implementations, consideration should be given to utilizing real data collected from various devices deployed in the power system. The proposed model has been introduced to address the limitations of existing systems. The outcomes validate the reliability of employing the K-Nearest Neighbours (KNN) model for managing Electric Vehicles (EVs) to ensure high accuracy. The KNN model successfully minimizes power losses, reduces voltage fluctuations, and achieves peak shaving by smoothing the load curve. In conclusion, the results highlight the performance metrics, including accuracy, precision, recall, and confusion matrix.

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