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Non-intrusive load classification for energy management of electrical appliances using convolutional long-short term memory

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Abstract

Non-intrusive load classification (NILC) is a crucial technique in energy management, helping to reduce unnecessary energy consumption and support the development of smart buildings. However, accurately classifying devices with similar characteristics and handling the complexity of electrical signals remain significant challenges. This research presents a deep learning-based NILC designed to efficiently extract key features from energy data. The convolutional LSTM combines a residual block (RB) and squeeze-and-excitation (SE) layers within a convolutional neural network (CNN) to enhance feature extraction while minimizing information loss. It consists of three main convolutional blocks, each incorporating SE layers to improve feature attention, along with long-short-term memory (LSTM) to capture sequential dependencies, leading to improved classification accuracy. The proposed model is trained on datasets containing 2, 3, and 4-electrical appliance operation scenarios, with feature data transformed into kurtograms to enhance signal characteristics. The training results achieved peak accuracy scores of 98.08%, 99.96%, and 99.75% and precision scores of 99.96%, 95.65%, and 97.10% for the respective scenarios. These results highlight the effectiveness of NILM in optimizing household energy usage, marking a significant step toward developing advanced technologies that reduce energy costs, promote sustainable energy consumption, and enhance energy management in future smart homes.

Keywords: Convolutional neural network, Deep learning, Long-short term memory, Non-intrusive load classification, Squeeze-and-excitation.

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1. Introduction

The management of household electricity consumption has gained widespread attention due to rising energy costs and the growing emphasis on energy efficiency. Numerous studies have explored the analysis of household electrical appliance energy consumption data to help users optimize their energy usage, reduce costs, and support economic and environmental sustainability. However, traditional energy monitoring methods, such as sensor-based systems that collect operational data, have limitations that can affect their effectiveness [1] face challenges related to high costs, complex installation, and maintenance difficulties. Consequently, research has shifted toward developing detection and classification techniques that rely on aggregate energy consumption data [2, 3] in conjunction with deep learning (DL) approaches [4]. These advancements have led to improved accuracy in energy classification and electrical appliance management, fostering innovative solutions that enhance the efficiency of energy analysis and consumption management.

The development of DL for classifying energy usage in electrical appliances has significantly enhanced the accuracy and efficiency of energy consumption analysis. For instance, Alden et al. [5] introduced an LSTM encoder-decoder to forecast energy production from solar panels, effectively utilizing smart meter data to separate energy sources under varying weather conditions while reducing the reliance on sensor installations. Chen et al. [6] improved home energy management efficiency using graph reinforcement learning by analyzing user behavior patterns through behavior correlation graphs, enabling optimal energy management strategies. Similarly, Nolasco et al. [7] proposed a CNN for detecting, extracting features, and performing multi-label classification of electrical loads in high-frequency signals. Their approach integrated YOLO networks with V-I trajectory analysis on field-programmable gate arrays to enhance parallel processing, allowing real-time detection and classification of multiple electrical appliances. Additionally, various DL frameworks, including ResNet50 [8], BiLSTM [9] and GRU [10], have been widely adopted to improve classification accuracy and expand practical applications in energy management.

However, the scalability of deep learning networks may be limited when classifying devices with similar energy consumption patterns, potentially leading to overfitting during training [11, 12]. To address this issue, this research explores the scalability of convolutional networks by enhancing their feature extraction capabilities through the expansion of convolutional layers, kernel layers, and activation functions. Additionally, the network (convolutional LSTM) combines residual layers to improve the reuse of extracted features, thereby reducing information loss. Including LSTM, which is used to learn the relationships in sequential data, allows the model to analyze energy consumption patterns of electrical appliances more accurately. The proposed method is evaluated using energy consumption data from 2, 3, and 4 electrical appliances, with the data processed through a kurtogram to emphasize key features of electrical signals. This approach aims to advance NILC technology, making it more efficient and applicable for household energy management.

2. Methods

2.1. Convolutional Neural Network

Convolutional neural network (CNN) [13] is a DL designed for extracting essential features. It utilizes convolutional layers with filters for feature extraction, followed by an activation function to introduce non-linearity. Additionally, max-pooling is employed to reduce the dimensionality while preserving the most significant features of the data. Through this process, the data is transformed into a vector and passed through a classification layer, where softmax is used for learning and classification. This research applies CNN due to its capability to extract critical features from complex data, enabling the analysis and classification of energy consumption patterns of electrical appliances, as in Equation 1.

$$A(i,j) = \sum_{m=0}^{f-1} \sum_{n=0}^{f-1} I(i+m, j+n) \cdot K(m,n) \quad (1)$$

Where I is an M × N image, K is the filter size for feature extraction, and A(i, j) denotes the pixel value at position (i,j). The convolutional operation is performed by passing the filter K(m, n) over I(i, j) and applying element-wise multiplication to the pixel values in the corresponding region of the image. The results of these multiplications are then summed to generate a feature map at position (i, j). Subsequently, the data is transformed into a vector and passed through the flatten layer and fully connected, as in Equation 2.

$$z = WX + b \quad (2)$$

Where W is the weight matrix, X is the input vector, and b is the bias term. The output is then passed through the softmax, which normalizes the values into probability distributions for classification.

2.2. Residual Blocks

Residual blocks (RB) [14] were developed by Microsoft Research to address the vanishing gradient problem in deep neural networks, allowing models to learn complex functions more efficiently. The core principle of RB is the use of skip connections or shortcuts, which enable direct data transfer from earlier layers to deeper layers, facilitating more effective gradient propagation. This study incorporates RB due to their ability to preserve essential features, mitigate gradient attenuation, and increase network depth without compromising performance, as in Equation 3.

$$y = F(x) + x \quad (3)$$

Where x is the input to the RB, F(x) is the learned transformation function, and y is the output of the block. As x passes through a convolutional layer, batch normalization, and an activation function, the resulting output F(x) is element-wise added to the original input x via a skip connection. If the dimensions of F(x) and x do not match, a convolution may be applied to x for dimensional alignment. This mechanism helps preserve crucial information, mitigates the vanishing gradient problem, and enables the model to learn more complex functions effectively.

2.3. Squeeze-and-Excitation

Squeeze-and-excitation (SE) [15] is a CNN module that enhances feature representation through channel-wise attention. It operates in three steps: Squeeze, which reduces spatial dimensionality using global average pooling; Excitation, which applies a two-layer fully connected network with ReLU and sigmoid activations to learn channel dependencies; and Recalibration, which rescales feature maps by multiplying them with the learned attention weights, enhancing important features while suppressing less relevant ones, as in Equation 4.

$$Z_C = \frac{1}{HxW} \sum_{ik=1}^{HW} X_C(i,j) \quad (4)$$

Where $X_C(i,j)$ is the pixel at position (i,j) in channel C; H and W are the spatial dimensions of the feature map obtained from C. The compressed channel representation, Z_C, is derived through channel compression. The resulting values are then processed through a learning mechanism to compute the attention weights for each channel.

2.4. Long Short-Term Memory

Long short-term memory (LSTM) [16] is a type of recurrent neural network (RNN) designed to address the vanishing gradient problem, a key limitation of traditional RNNs. LSTM efficiently retains important information from long sequences through three key mechanisms: the forget gate, which controls which information to retain or discard; the input gate, which selects new information to add to memory cells; and the output gate, which determines the final output of the network. These capabilities make LSTM particularly effective for tasks involving sequential data.

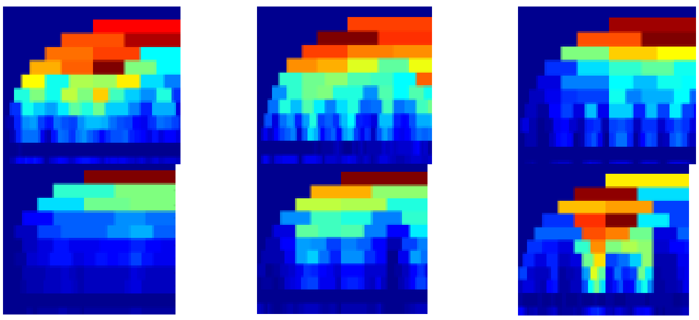
3. Proposed

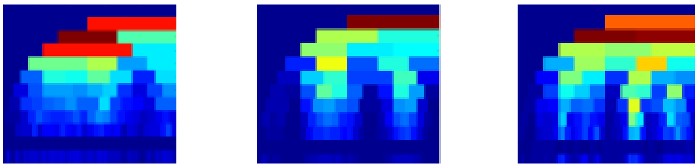
3.1. Dataset

This study utilizes a dataset that records the operation of electrical equipment within a building, developed to monitor electrical loads without requiring additional installation at each usage point [17]. The data were collected in real time and include details of five types of electrical equipment: a 7,033-watt air conditioner (Appliance 1), a 3,516-watt air conditioner (Appliance 2), a 28-watt light bulb (Appliance 3), an 800-watt microwave oven (Appliance 4), and a 150-watt water pump (Appliance 5). Data recording was conducted using a programmable logic device capable of accurately sampling operational signals, with each device sampling 1,000 data points (ON and OFF). The recorded data were analyzed under three different cases.

- 2-Electrical Appliances: Combinations of two electrical appliances, including data12, data15, data25, data34, and data45.
- 3- Electrical Appliances: Combinations of three electrical appliances, including data124, data135, data145, data235, and data345.
- 4- Electrical Appliances: Combinations of four electrical appliances, including data1234, data1235, data1245, data1345, and data2345.

In this study, the behavioral patterns of each electrical appliance were converted into a Kurtogram [18], as in Figure 1, to transform the data structure into a form suitable for analysis. The processed data were then split into 80% for training and 20% for testing to develop and evaluate the performance of the model in classifying the energy consumption behavior of electrical appliances.





2- Electrical Appliances 3- Electrical Appliances 4- Electrical Appliances

Figure 1.
Kurtogram image.

3.2. Proposed Convolutional LSTM Architecture

This study adapts a CNN structure [19] to extract deep features of electrical appliance performance characteristics, emphasizing the integration of convolutional layers, RB, and SE, as shown in Figure 2.

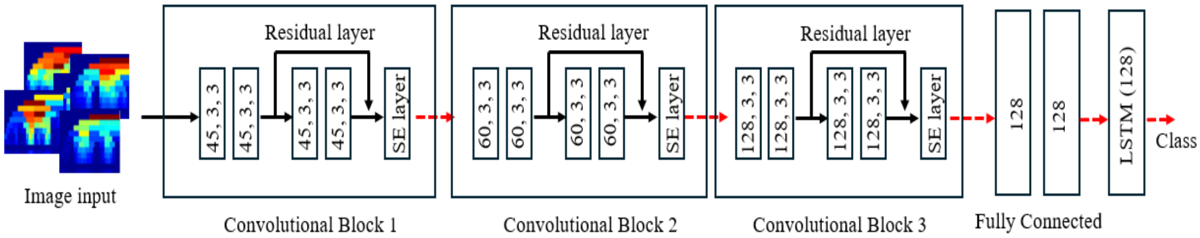


Figure 2.
Proposed method.

The operation of the proposed network is illustrated in Figure 2. The process begins with convolutional block 1, which utilizes a (45,3,3) filter and incorporates a cross-connected residual block to mitigate the vanishing gradient problem, along with a squeeze-and-excitation layer to enhance feature importance. This block extracts initial feature representations and forwards them to the convolutional block 2, which maintains a similar structure but increases the filter size to (60,3,3) to capture more complex characteristics of the electrical power data.

Next, the extracted data enters convolutional block 3, which utilizes a (123,3,3) filter while continuing to incorporate the RB and SE layers to enhance the model's capability in learning deep structural features. Once the convolution process is complete, the extracted features are transformed into vectors and passed through fully connected layers consisting of two layers with 128 neurons to synthesize information and learn complex electrical energy consumption patterns. Finally, the processed data is forwarded to the Output Layer, which is then passed through an LSTM layer with 128 units to classify electrical appliances. This architecture enables the model to effectively analyze and interpret the energy consumption behavior of electrical appliances.

3.3. Evaluation

This study utilizes accuracy and precision as key indicators for a comprehensive analysis, as in Equations 5 and 6. Additionally, a confusion matrix is employed to assess classification accuracy and analyze error trends in identifying the operating states of electrical appliances.

$$\text{Accuracy} = \frac{\text{TP+FN}}{\text{TP+FP+FN+TN}} \qquad (5)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (6)$$

When true positive (TP) and true negative (TN) are correctly classified appliance states, TP for correct operation predictions and TN for correct non-operation predictions. Conversely, false positives (FP) and false negatives (FN) are misclassified operational states.

4. Experimental Results

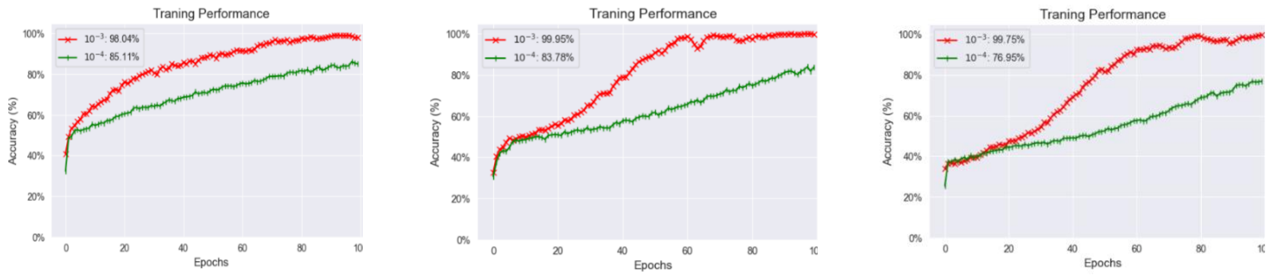
This section covers training parameters, defining the hardware setup and DL libraries; training results, training performance for electrical appliances; and performance classification, using a confusion matrix to assess classification accuracy.

4.1. Parameters of Training Model

The experiments were conducted on a Windows computer with an Intel Core i5-12400F CPU, 32 GB RAM (5,600 MHz), and an NVIDIA RTX 4070 (12 GB VRAM, 5,888 CUDA cores) for network training acceleration. The model was developed and tested using NumPy and TensorFlow. Standardized training parameters included a 100×100×3 input image size, 10^{-3} and 10^{-4} learning rate, 100 epochs, 128 batch size, categorical crossentropy loss function, and Adam optimizer for parameter tuning.

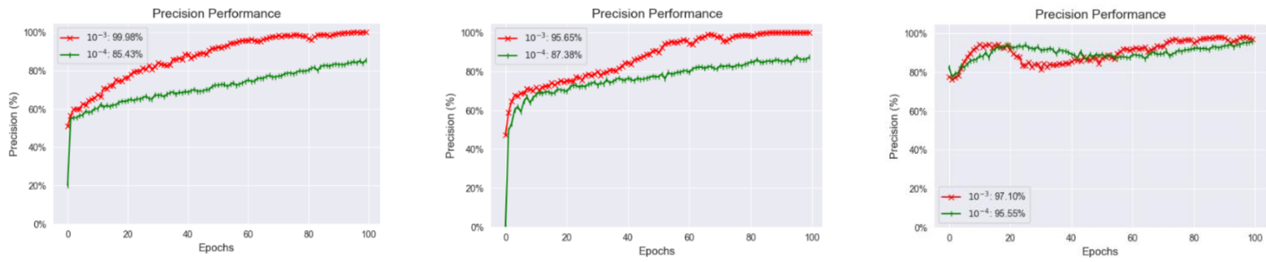
4.2. Training Performance

In Figure 3, the training results of the model using learning rates of 10^{-3} and 10^{-4} on combined electrical device operation datasets containing 2, 3, and 4-electrical appliances. The results indicate that the model with a learning rate of 10^{-3} achieves higher accuracy and converges faster than the one with 10^{-4}. However, as the number of electrical appliances increases, the growing data complexity reduces training accuracy, limiting the model's ability to extract device operation features.



(a) 2 Electrical appliances. (b) 3 Electrical appliances. (c) 4 Electrical appliances.

Figure 3.
Accuracy performance of training model.



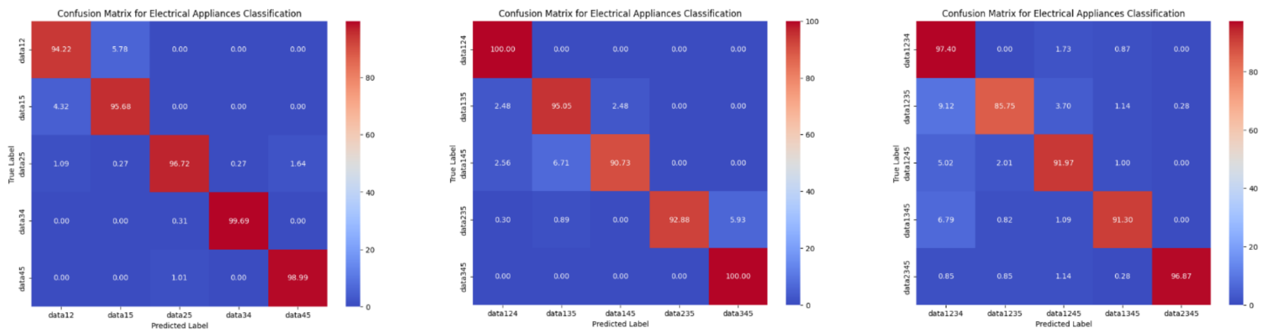
(a) 2 Electrical appliances. (b) 3 Electrical appliances. (c) 4 Electrical appliances.

Figure 4.
Precision performance of the training model.

Figure 4, the precision results of the training model indicate that a learning rate of 10^{-3} achieves the highest precision values of approximately 99.98%, 95.65%, and 97.10%, while the model with a learning rate of 10^{-4} attains maximum precision values of 85.43%, 87.38%, and 95.55%.

4.3. Classification Performance

In Figure 5, the Confusion Matrix for classifying 2, 3, and 4 electrical appliances. The results indicate that as the number of devices increases, the model's accuracy tends to decline. For instance, in the case of 2 electrical appliances, the model achieves high classification accuracy, ranging from 94% to 99%, with only minor errors. An example is data12 being misclassified as data15 at a rate of 5.78%. However, when tested with 3 electrical appliances, errors begin to increase, such as data145 being misclassified as data135 at 6.71%, indicating that the growing complexity of the data leads to confusion in the model. Furthermore, in the case of 4 electrical appliances, the error rate rises even further, with examples such as data1235 being misclassified as data1234 at 9.12% and data1245 being misclassified as data1235 at 5.02%. This increased misclassification is due to the similar characteristics of the devices, making it more challenging for the model to accurately distinguish between them.



(a) 2 Electrical appliances (b) 3 Electrical appliances (c) 4 Electrical appliances

Figure 5.
Results of electrical appliances classification.

5. Discussion

The convolutional LSTM is designed to enhance the classification of electrical appliances based on functional data by combining RB and SE into a CNN. This combination allows the model to effectively emphasize important features of electrical appliances. The model architecture consists of 3 convolutional blocks, where RB helps preserve the original features and minimizes the loss of deep information, while SE enhances deep patches by passing data through fully connected layers. Additionally, an LSTM (128 units) is incorporated to extract functional characteristics of electrical appliances for more accurate classification. The experiment utilizes data transformed using the kurtogram, which enhances the distinctiveness of electrical appliances' features. This transformation enables the model to better learn the data structure, leading to improved performance in NILC.

The experimental results indicate that the model with a learning rate of 10^{-3} learns faster and achieves higher accuracy compared to 10^{-4}. However, when classifying a larger number of devices, such as four, the model's accuracy tends to decline, likely due to the increased data complexity, which leads to confusion in device classification. Additionally, the confusion matrix analysis shows that while the model effectively classifies devices with distinct characteristics, it struggles with those that have similar properties. Nevertheless, the integration of RB and SE helps the model extract important features and mitigate data loss effectively. Therefore, the proposed network can serve as a valuable framework for advancing non-intrusive load monitoring in smart energy management, reducing unnecessary energy consumption, and enhancing the efficiency of energy monitoring systems for various devices in smart buildings.

The proposed NILC model can be seamlessly integrated into modern Energy Management Systems (EMS) [20, 21] to enhance the real-time monitoring and control of household or building electrical loads. By accurately classifying the operating status of individual appliances using aggregated energy consumption data, the system enables dynamic load management without the need for intrusive sensors. This integration allows EMS to automatically execute intelligent actions such as scheduling device operation during off-peak hours, shutting down idle appliances, or issuing alerts when abnormal consumption patterns are detected.

Furthermore, the NILC framework supports long-term energy analytics by identifying usage trends and inefficiencies, contributing to the development of predictive maintenance and personalized energy-saving recommendations. As a result, the incorporation of the NILC model into EMS fosters energy efficiency, reduces operational costs, and promotes sustainable consumption, aligning with the goals of smart grid and smart home technologies.

6. Conclusion

This research proposes a DL-based NILC to improve the management of energy consumption in electrical appliances. The convolutional LSTM is enhanced with convolutional layers, kernel layers, and activation functions. Additionally, it combines a residual block to improve the reuse of residual data from feature extraction and incorporates an LSTM to classify electrical appliances. Experiments involving the classification of 2, 3, and 4 electrical appliances are conducted to evaluate the efficiency of the proposed network.

The convolutional LSTM was trained on combining data from electrical appliances, achieving the highest training accuracy of 98.08%, 99.96%, and 99.75%, along with the highest overall training precision of 99.96%, 95.65%, and 97.10% for interactions involving 2, 3, and 4 electrical appliances, respectively. Furthermore, the network demonstrated strong classification performance in the confusion matrix, achieving peak accuracies of 94.22%, 95.68%, 96.72%, 99.69%, and 98.99% for 2 appliances; 100.0%, 95.05%, 90.73%, 92.88%, and 100% for 3 appliances; and 97.40%, 85.75%, 91.97%, 91.30%, and 96.87% for 4 appliances. These results highlight the model's ability to effectively learn and classify complex device behaviors.

The experimental results from the proposed method for classifying electrical appliance performance demonstrate balanced accuracy, highlighting its potential to enhance NILM. This improvement increases the network's capability, making it more suitable for real-time applications in energy management within smart building systems.

References

[1] I. Abubakar, S. Khalid, M. Mustafa, H. Shareef, and M. Mustapha, "An overview of non-intrusive load monitoring methodologies," presented at the 2015 IEEE Conference on Energy Conversion (CENCON), 2015.

[2] Y. Liu, J. Qiu, and J. Ma, "SAMNet: Toward latency-free non-intrusive load monitoring via multi-task deep learning," *IEEE Transactions on Smart Grid,* vol. 13, no. 3, pp. 2412-2424, 2021. https://doi.org/10.1109/TSG.2021.3139395

[3] H. Rafiq, X. Shi, H. Zhang, H. Li, M. K. Ochani, and A. A. Shah, "Generalizability improvement of deep learning-based non-intrusive load monitoring system using data augmentation," *IEEE Transactions on Smart Grid*, vol. 12, no. 4, pp. 3265-3277, 2021. https://doi.org/10.1109/TSG.2021.3082622

[4] R. Machlev, A. Malka, M. Perl, Y. Levron, and J. Belikov, "Explaining the decisions of deep learning models for load disaggregation (NILM) based on XAI," presented at the 2022 IEEE Power & Energy Society General Meeting (PESGM), 2022.

[5] R. E. Alden, H. Gong, E. S. Jones, C. Ababei, and D. M. Ionel, "Artificial intelligence method for the forecast and separation of total and hvac loads with application to energy management of smart and nze homes," *Ieee Access*, vol. 9, pp. 160497-160509, 2021. https://doi.org/10.1109/ACCESS.2021.3129172

[6] X. Chen, T. Yu, Z. Pan, Z. Wang, and S. Yang, "Graph representation learning-based residential electricity behavior identification and energy management," *Protection and Control of Modern Power Systems*, vol. 8, no. 1, p. 28, 2023. https://doi.org/10.1186/s41601-023-00305-x

[7] L. S. Nolasco, A. E. Lazzaretti, and B. M. Mulinari, "DeepDFML-NILM: A new CNN-based architecture for detection, feature extraction and multi-label classification in NILM signals," *IEEE Sensors Journal*, vol. 22, no. 1, pp. 501-509, 2021. https://doi.org/10.1109/JSEN.2021.3127322

[8] T. Chen, H. Qin, X. Li, W. Wan, and W. Yan, "A non-intrusive load monitoring method based on feature fusion and SE-ResNet," *Electronics*, vol. 12, no. 8, p. 1909, 2023. https://doi.org/10.3390/electronics12081909

[9] P. Lalwani and R. Ganeshan, "A novel CNN-BiLSTM-GRU hybrid deep learning model for human activity recognition," *International Journal of Computational Intelligence Systems*, vol. 17, no. 1, pp. 1-20, 2024.

[10] I. Jrhilifa, H. Ouadi, A. Jilbab, S. Gheouany, N. Mounir, and S. El Bakali, "Vmd-gru based non-intrusive load monitoring for home energy management system," *IFAC-PapersOnLine*, vol. 58, no. 13, pp. 176-181, 2024. https://doi.org/10.1016/j.ifacol.2024.07.479

[11] Z. Fang, D. Zhao, C. Chen, Y. Li, and Y. Tian, "Nonintrusive appliance identification with appliance-specific networks," *IEEE Transactions on Industry Applications*, vol. 56, no. 4, pp. 3443-3452, 2020. https://doi.org/10.1109/TIA.2020.2994279

[12] M. Muaz, I. Zinnikus, and M. Shahid, "NILM domain adaptation: When does it work?," presented at the 2024 10th International Conference on Smart Computing and Communication (ICSCC), 2024.

[13] Z. Loukil and A.-M. Salah, "Toward hybrid deep convolutional neural network architectures for medical image processing.," presented at the 2020 International Conference on Innovation and Intelligence for Informatics, Computing and Technologies (3ICT), 2020.

[14] C.-L. Li and C.-Y. Su, "Multi-connection of double residual block for YOLOv5 object detection," presented at the 2022 8th International Conference on Applied System Innovation (ICASI), 2022.

[15] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 7132-7141.

[16] A. Tongta and K. Chooruang, "Long short-term memory (LSTM) neural networks applied to energy disaggregation," in *2020 8th International Electrical Engineering Congress (iEECON)*, 2020: IEEE, pp. 1-4.

[17] S. Yaemprayoon and J. Srinonchat, "Exploring CNN model with inrush current pattern for non-intrusive load monitoring," *Computers, Materials & Continua*, vol. 73, no. 2, pp. 3667–3684, 2022. https://doi.org/10.32604/cmc.2022.028358

[18] J. Antoni, "The spectral kurtosis: A useful tool for characterising non-stationary signals," *Mechanical Systems and Signal Processing*, vol. 20, no. 2, pp. 282-307, 2006. https://doi.org/10.1016/j.ymssp.2004.09.001

[19] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proceeding International Conference Learning Representations (ICLR), San Diego, USA, May 7–9, 2015*, 2014.

[20] L. Xu, L. Xia, S. Wang, J. Zheng, S. LI, and Q. Zhang, "Research on building energy system management system based on new power system under carbon peaking and carbon neutrality goals," presented at the 2024 IEEE 8th Conference on Energy Internet and Energy System Integration (EI2), 2024.

[21] A. B. El-Fawair, K. M. Al-Aubidy, and M. A. Al-Khawaldeh, "Energy management in microgrids with renewable energy sources and energy storage system," presented at the 2023 20th International Multi-Conference on Systems, Signals & Devices (SSD), 2023.