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Development of hybrid CNN-LSTM for non-intrusive load monitoring

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Abstract

Non-Intrusive Load Monitoring (NILM) is a technique used to distinguish the energy consumption of individual electrical devices from aggregated energy consumption data without requiring additional sensors on each device. This technology plays a crucial role in efficient energy management, reducing energy costs, and supporting the development of smart buildings. This research focuses on developing a hybrid deep learning network to enhance NILM efficiency by combining convolutional neural networks with long short-term memory networks. This combination enables the analysis of complex electrical power signals, improving the accuracy of device classification, reducing prediction errors, and enhancing learning efficiency from diverse data. The proposed method is trained using electrical appliance interaction data in three configurations: 2-appliance, 3-appliance, and 4-appliance interactions. Experimental results demonstrate training accuracies of 98.59%, 98.59%, and 93.09%, respectively, while the highest testing accuracies are 98.59%, 95.61%, and 92.94%. These results highlight the potential for further advancements in NILM technology, enabling more efficient energy monitoring systems and promoting sustainable energy use in the future.

Keywords: Artificial intelligence, Convolutional neural networks, Deep learning, Long short-term memory, Non-intrusive load monitoring.

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1. Introduction

In the present, household electricity consumption has become a significant area of study, utilizing data on the energy usage of various electrical appliances to analyze and assist users in optimizing their energy consumption behavior. This, in turn, impacts costs and promotes economic sustainability. However, traditional electricity usage monitoring relies on installing sensors alongside devices capable of learning operational patterns, known as Intrusive Load Monitoring (ILM) [1]. This method has several limitations, such as high costs, complex installation processes, and maintenance difficulties. Consequently, an alternative approach, Non-Intrusive Load Monitoring (NILM), has been developed to address these challenges [2, 3].

NILM relies on analyzing the total energy consumption data of all appliances, including parameters such as current, voltage, frequency, and others. This approach is combined with signal processing techniques or deep learning (DL) Machlev, et al. [4] to distinguish different load operation patterns. The development of deep learning techniques in recent years has significantly improved the accuracy and efficiency of load monitoring Yang, et al. [5] particularly through convolutional neural networks (CNNs), which effectively learn the characteristic features of electrical appliances. For Yin and Ma [6] proposed an NILM model utilizing IVCRACNN, which integrates MobileNet as the backbone to reduce computational complexity. This model employs depth-wise separable convolution to separate processing across channels and minimize the number of parameters. The system was tested using voltage-current waveforms, transformed through a transferring method, and trained for NILM. Similarly, Yang, et al. [7] developed an NILM model using Temporal Convolutional Networks (TCN) and dilated causal convolution to address visibility limitations and enhance the model's ability to learn sequential information. The model also incorporates Residual connections to mitigate the gradient vanishing problem, working alongside activation functions to preserve electrical load characteristics more effectively. In Ciancetta, et al. [8] proposed a CNN-based NILM model designed to detect and classify electrical loads simultaneously without requiring prior event segmentation, thereby reducing computational time. This approach was tested using the Short-Time Fourier Transform (STFT) of electrical currents, represented as a 101×26 matrix (frequency×time). The transformed data was processed through a convolutional layer with filters of sizes 32, 64, and 32, utilizing ReLU activation and max pooling to downsize features and decrease computational costs. Other studies, such as Zhang, et al. [9] and Su, et al. [10] have also explored NILM advancements. However, using a single deep neural network still has limitations in terms of accuracy, particularly due to the complexity of capturing the operational characteristics of highly intricate electrical devices. This challenge often results in load recognition errors Fang, et al. [11] and overfitting issues during training, especially when recognizing similar electrical appliances [12].

Based on the aforementioned research approaches, this study focuses on developing a Hybrid Deep Learning (Hybrid DL) network that integrates the advantages of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) to enhance the efficiency of NILM. The proposed hybrid model improves accuracy in distinguishing complex loads and reduces misclassification errors in electrical appliance identification. Additionally, the model incorporates Residual blocks and AL to enhance training efficiency and improve result consistency in learning. The proposed model is evaluated using three different scenarios of appliance operation: the simultaneous operation of 2- appliances, 3- appliances, and 4-appliances. The operational data is processed through a Kurtogram to highlight essential features of electrical signals more distinctly. This research provides a significant contribution to advancing NILM technology, improving its accuracy and effectiveness. Moreover, it supports the development of sustainable energy consumption analysis for the future.

2. Research Theory

This section compiles the theories used in the experiment, including details on their operation and application in the experiment, as follows.

2.1. Convolutional Neural Network

A CNN Prommakhot and Srinonchat [13] is a deep learning architecture designed for analyzing and learning features from images using convolutional layers. These layers extract essential features through filters, followed by the ReLU activation function to introduce non-linearity, and max-pooling layers to reduce data dimensions while preserving key features. The processed data is then transformed into a vector through a fully connected layer, where Softmax is used for classification.

The learning process of CNN consists of forward propagation, loss calculation, and backpropagation, which adjust parameters for optimal performance. This study integrates CNN due to its capability to extract features from electrical device operations. The details of its functionality are as follows:

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

Let I be an image of size MxN and K be a filter of size fxf used for feature extraction. The output $O(i,j)$ at position (i, j) on the feature map is obtained by sliding the filter $K(m,n)$ across the image $I(i,j)$. This process involves element-wise multiplication between the filter values and the corresponding pixel values in the image. The results are then summed to produce the feature map at position (i,j). This step is crucial for extracting distinctive features from the image.

2.2. Long Short-Term Memory Network

The Long Short-Term Memory (LSTM) network Mao, et al. [14] is designed to address the vanishing gradient problem in learning sequential data with long dependencies. LSTM utilizes a memory cell structure, which consists of a Forget Gate

(Equation 2), an Input Gate (Equations 3 and 4), an Update Cell State (Equation 5), and an Output Gate (Equations 6 and 7). These components work together to regulate the flow of information.

The Forget Gate determines whether past information should be discarded or retained.

The Input Gate decides whether new information should be added to the memory cell.

The Output Gate determines which part of the information in the memory cell should be output.

This study incorporates LSTM due to its capability to emphasize essential features in long-sequence data. The detailed operation is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$
$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{5}$$
$$O_t = \sigma(W_O \cdot [h_{t-1}, x_t] + b_O) \tag{6}$$
$$h_t = O_t \tanh(C_t) \tag{7}$$

When f_t is the output of the Forget Gate, and W_f and b_f represent the weight and bias of the Forget Gate, respectively, h_{t-1} denotes the hidden state, and x_t is the new input data. Meanwhile, i_t is the output of the Input Gate, and $\tilde{C}_t$ represents the new cell state, which is processed through the tanh activation function to aggregate the updated memory values.

The cell state is C_t influenced by both the previous memory state C_{t-1} and the newly added information. This updated memory is then passed to the Output Gate, which produces an output value O_t, regulating the flow of information from the memory cell. The hidden state h_t represents the output of the LSTM, which is then propagated to the next layer of the network.

2.3. Residual Blocks

Residual Blocks (RB) Zhang, et al. [15] were developed by Microsoft research to mitigate the vanishing gradient problem in deep learning models, enabling neural networks to learn deep functions more effectively. This study integrates RB due to their capability to preserve important information and prevent its loss. The detailed operation is as follows:

$$y = F(x) + x \tag{8}$$

When x is the input, $F(x)$ is the learning function, and y is the output of the RB, the result is a patch from the previous layer, which is then added back into the computation for the next layer.

2.4. Attention Layers

Attention layers (AL) Tan and Ding [16] are designed to help the model focus on important information rather than treating all data equally. AL relies on self-attention to compute the relationships between data positions, as shown in Equation 9. This mechanism enables the model to learn essential features more effectively. The output is represented as data that reflects the learned attention weights. This study integrates AL into the development process due to its ability to preserve the relationships and significance of the data. The detailed working mechanism is as follows:

$$\text{Attention (AL)} = \text{Softmax}\left(\frac{\text{QK}^{\text{T}}}{\sqrt{\text{d}_\text{x}}}\right)\text{V} \tag{9}$$

When Q, K, and V represent the query, key, and value matrices, respectively, and d_x is the dimension of the key, the output is a matrix that represents the data weighted according to the importance learned by the model.

3. Methodology

This research proposes the development of a hybrid model for NILM. The work is divided into three parts: Part 1, the NILM dataset is a data that has been transformed into a Kurtogram to highlight the performance characteristics of electrical appliances. Part 2, the integration of a CNN network with the ability to extract deep features of energy signals and an LSTM to analyze the time sequence of energy consumption. Such fusion enables the network to effectively learn the energy patterns and behaviors of electrical appliances, and also helps the model to reduce the problem of incorrect load separation. In addition, the RB layer and AL are fused to emphasize the features of the data. Finally, the precision, recall, accuracy, Mean Absolute Error (MAE), and confusion matrix are evaluated for the proposed method and compared with previous methods.

3.1. Dataset

This study uses the indoor electrical appliance operation dataset, which is developed for NILM Yaemprayoon and Srinonchat [17]. The dataset records real-time energy values and details of five electrical appliances: a 7,033-watt air conditioner (device 1), a 3,516-watt air conditioner (2-appliance), a 28-watt light bulb (3-appliance), an 800-watt microwave oven (4-appliance), and a 150-watt water pump (5-appliance). The operation data of the appliances are recorded using a programmable logic device with sampling accuracy. The recording characteristics of the equipment are: 1 device records 1000 times (ON/OFF). This study studies three types of data:

1) 2-appliance e combination: 12, 15, 25, 34 and 45.
2) 3-appliance combination: 124, 135, 145, 235 and 345.
3) 4-appliance combination: 1234, 1235, 1245, 1345 and 2345.

The combination of these three characteristics is transformed into a Kurtogram Antoni [18] to change the characteristics of the data as shown in Figure 1. The image data is collected and grouped for training 80% and testing 20%.

The Kurtogram image shows the compatibility of 2-appliance.

The Kurtogram image shows the compatibility 3-appliance.

The Kurtogram image shows the compatibility of 4-appliance.

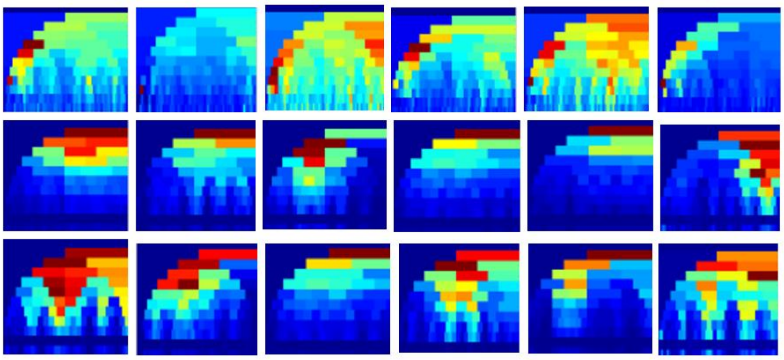

Figure 1.
The Kurtogram illustrates the interaction between electrical devices.

3.2. Hybrid Deep Learning

Table 1, the proposed hybrid deep learning development application CNN extracts deep functions from electrical functions through spiral layers and max pooling, and integrates LSTM transmission function to learn data change patterns.

Table 1. Outlines the operation.

Table 1
Hybrid CNN-LSTM for non-intrusive load monitoring

Algorithms: CNN-LSTM with Residual blocks and AL.
STEP 1: Load the required libraries: Import TensorFlow, NumPy, Matplotlib, and OS for model development and data management.
STEP 2: Define dataset paths: Specify paths for training and testing datasets.
STEP 3: Define image parameters: Image size, batch size and appliance interactions.
STEP 4: Data preprocessing and augmentation: Apply necessary transformations to enhance training and test datasets.
STEP 5: CNN-LSTM model design:
STEP 5.1: The convolution operator as in Equation 1: convolution is structured into 3 layers (1 block). The network consists of 3 blocks with convolutional filter sizes of 32, 64, and 128. A 3×3 kernel is applied with ReLU activation and SAME padding to maintain the spatial dimensions.
STEP 5.2: MaxPooling with a 2×2 filter is applied at each block to reduce spatial dimensions. The feature maps are then passed through a dense layer with 128 units.
STEP 5.3: Reshape feature maps for LSTM: In Equations 2 to 7 the extracted features are reshaped into sequential data format to prepare for LSTM processing.
STEP 5.4: Pass features through LSTM: The LSTM layer has 64 memory units to capture sequential relationships in the data.
STEP 5.5: The output is passed through a Softmax function to predict the probability distribution over device operations.
STEP 5.6: The model is trained using the Adam optimizer with a learning rate of 10^{-4}, ensuring stable parameter updates during training.
STEP 6: CNN-LSTM model with Residual Blocks and Attention Mechanisms for improved feature learning.
STEP 6.1: CNN-LSTM with RB: In Equation 8 RB is incorporated between the first and third convolutional blocks to mitigate vanishing gradient issues. The feature maps from the first block are added to the output of deeper layers.
STEP 6.2: CNN-LSTM with AL: In Equation 9 AL is integrated between the convolutional layers and LSTM to selectively focus on the most relevant features, enhancing the model's ability to learn important patterns. The attention mechanism is defined with Q, K, and V set to 128, allowing the network to capture dependencies across different regions. The attention module employs 4 attention heads, each with a head size of 128, enabling parallel feature extraction and improving the model's ability to process spatial and sequential information effectively.
STEP7: Evaluates the training results by comparing the performance of CNN-LSTM, CNN-LSTM with RB, CNN-LSTM with AL.
STEP 8: Final steps.

3.3. Performance Measurement

This study applied precision, accuracy, recall, and MAE to comprehensively evaluate the results, such as Equations 10, 11, 12, and 13, as well as a fusion matrix to display the variance of device operation classification.

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{FN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN} + \mathrm{TN}} \tag{10}$$

$$\mathrm{Precision} \frac{\mathrm{TP}}{= \mathrm{TP} + \mathrm{FP}} \tag{11}$$

$$\mathrm{Recall} \frac{\mathrm{TP}}{= \mathrm{TP} + \mathrm{FN}} \tag{12}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{i}=1}^{\mathrm{n}} |\mathrm{y_i} - \hat{\mathrm{y}}_{\mathrm{i}}| \tag{13}$$

True Positive (TP) and True Negative (TN) represent the number of correctly classified samples, while False Positive (FP) and False Negative (FN) indicate the number of misclassified samples. Let n be the number of samples in the dataset, y_i be the actual value of the i-th sample, and $\hat{y}_i$ be the predicted value of the i-th sample. The MAE describes the average error of the model in terms of the predicted variable's units.

4. Results

In this section are divided into 3 parts: 1) Experimental parameters, including the training computer settings and the DL library used for training the network; 2) Training results, describing the effectiveness of the proposed network in training to learn data characteristics; 3) Device behavior classification, showing the results in the form of confusion matrix for comparing the classification results.

4.1. Training parameters

A computer that conducts experiments on a windows operating system equipped with Intel core i5-12400f LGA 1700 @ 2 processor. 5 GHz, with 32 GB of RAM and 5600 MHz speed, and trained with NVIDIA RTX 4070, with 12 GB of VRAM and 5,888 CUDA cores. NumPy and TensorFlow are used as network design tools, including network testing. The training parameters are defined as standardization in Table 2.

Table 2.
Parameter of training model.

Parameter	**Value**
Image size	100x100x3
Learning rate	10^{-4}
Epoch	150
Batch size	64
Loss function	Categorical cross-entropy
Optimization	Adam

4.2. Training results

Tables 3, 4, and 5 present the training results, including precision, recall, and accuracy in testing, as well as MAE and the training time for each model. The experimental results demonstrate the effectiveness of CNN-LSTM, CNN-LSTM with Residual, and CNN-LSTM with AL in enhancing network performance. Among these models, CNN-LSTM achieves a favorable MAE and demonstrates its ability to learn complex data patterns. The addition of RB connections further improves the model's capacity to handle complex data, as indicated by a continuous decrease in MAE. Notably, when applied to three devices, the MAE reaches 0.0171. The results indicate that integrating both RB and AL mechanisms enhance performance, achieving a balanced outcome between training efficiency, test accuracy, and training time.

Table 3.
Results of the operation of 2-appliances.

Model	**Precision (Training)**	**Recall (Training)**	**Accuracy (Testing)**	**MAE**	**Time (Minute)**
CNN-LSTM	98.21 %	98.21 %	96.35 %	0.0144	16.15
CNN-LSTM with Residual	98.59 %	98.59 %	98.59 %	0.0059	20.76
CNN-LSTM with Attention	98.40 %	98.40 %	98.40 %	0.0068	16.03

Table 4.
Results of the operation of 3-appliances.

Model	Precision (Training)	Recall (Training)	Accuracy (Testing)	MAE	Time (Minute)
CNN-LSTM	82.37 %	79.02 %	81.06 %	0.0996	14.30
CNN-LSTM with Residual	95.61 %	95.61 %	95.61 %	0.0171	18.19
CNN-LSTM with Attention	95.04 %	94.98 %	95.04 %	0.0199	14.62

Table 5.
Results of the operation of 4-appliances.

Model	Precision (Training)	Recall (Training)	Accuracy (Testing)	MAE	Time (Minute)
CNN-LSTM	89.91 %	82.51 %	80.54 %	0.0918	14.76
CNN-LSTM with Residual	92.12 %	92.07 %	92.07 %	0.0320	18.69
CNN-LSTM with Attention	93.09 %	92.71 %	92.94 %	0.0310	14.87

4.3. Test Results

Tables 3, 4, and 5 were tested using a confusion matrix, as shown in Figure 2, to evaluate classification performance. The results indicate high accuracy in distinguishing different device operations. However, some cases exhibit minor misclassification. For instance, in the classification of 2-appliances, misclassification occurred between data12 and data15. Similarly, in the classification of 4-appliances, misclassification was observed in data1234, data1235, data1245, and data1345, with lower classification performance compared to other device operations. This variability suggests that the classification errors may stem from the similarities in power consumption patterns among certain devices, leading to overlapping feature representations and misclassification.

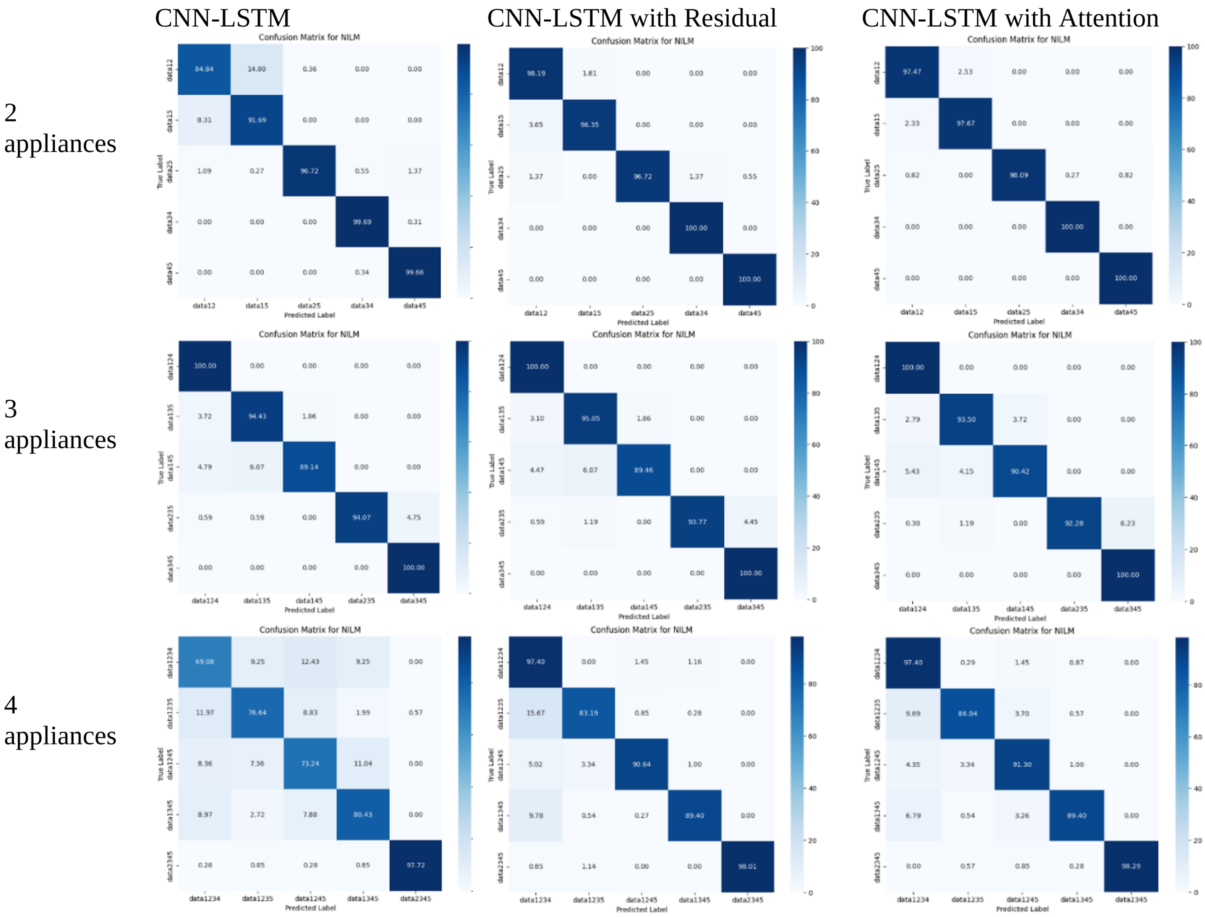

Figure 2.
Results of appliance operation classification.

5. Discussion

This research presents a hybrid deep learning model that integrates the capabilities of CNN and LSTM to enhance the accuracy of NILM. The proposed approach aims to reduce classification errors in electrical device identification while improving the model's ability to handle complex data. The incorporation of RB and AL in the model ensures a balance between learning efficiency and stable training. The proposed design follows the methodologies of Zhu [19] and Zhang

[20]. The model was tested using data from the operation of 2-appliances, 3-appliances, and 4-appliances, leveraging Kurtogram analysis to emphasize key features of electrical signals [17]. This approach contributes to improving the accuracy and effectiveness of NILM technology. From the experimental results, an analysis of the outcomes reveals that CNN-LSTM performs worse than all other models, particularly in Table 3, where it achieved a test accuracy of 81.06% and the highest MAE of 0.0996. This indicates that the baseline model struggles to learn complex data patterns effectively, despite its shorter training time. In contrast, CNN-LSTM with RB demonstrates improved performance and significantly reduces MAE. This suggests that integrating RB connections enhances the model's ability to learn complex data and improves classification accuracy. However, adding RB connections increases training time, especially when analyzing the operation of 2-appliances and 4-appliances. Meanwhile, CNN-LSTM with Attention excels in balancing accuracy and training time. As shown in Table 5, this model achieved the highest test accuracy of 92.94% and the lowest MAE of 0.0310, indicating effective learning without requiring as many computational resources as the RB model. Furthermore, when analyzing the operation of 3-appliances, the Attention-based model achieved 95.04% accuracy, slightly lower than the 95.61% accuracy of the RB model. However, the AL model required significantly less training time, demonstrating that the AL mechanism enhances accuracy while optimizing resource usage during training.

6. Conclusion

This research proposes a hybrid CNN-LSTM model for NILM. The proposed network consists of three variations: CNN-LSTM, CNN-LSTM with Residual, and CNN-LSTM with AL, designed for classifying electrical devices. The experiments were conducted with different combinations of electrical device operations, including 2-appliance, 3-appliance, and 4-appliance scenarios. To ensure standard evaluation, precision, recall, accuracy, MAE, and training time were used to assess the performance of the proposed networks. The proposed network was trained using data from the operation of multiple electrical devices. The experimental results demonstrate that the model achieved training accuracies of 98.59%, 98.59%, and 93.09%, and the highest test accuracies of 98.59%, 95.61%, and 92.94% for 2-appliance, 3-appliance, and 4-appliance scenarios, respectively. These results highlight the model's capability to learn complex data patterns effectively. The findings suggest that the Hybrid CNN-LSTM approach is an effective method for improving the classification of electrical device operations, striking a balance between accuracy and computational efficiency. Additionally, the study provides insights into further enhancing NILM technology, enabling its practical application in smart building energy management systems.

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