A CNN–LSTM Architecture with Residual and Squeeze-and-Excitation Blocks for Scenario-Based Non-Intrusive Load Identification

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ABSTRACT

Non-Intrusive Load Identification (NILI) is a crucial technique in energy management, enabling the reduction of unnecessary energy consumption and supporting the development of smart building systems. Nevertheless, accurately distinguishing electrical appliances with similar operational characteristics and addressing the complexity of aggregated electrical signals are challenging tasks. This study proposes a deep learning-based NILI framework designed to effectively extract discriminative features from energy consumption data. The proposed Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture incorporates Residual Blocks (RB) and Squeeze-and-Excitation (SE) blocks to enhance feature representation while alleviating information loss during deep feature propagation. The network comprises three convolutional blocks with integrated SE layers to strengthen channel-wise feature attention, followed by an LSTM module that captures long-term temporal dependencies in sequential energy signals. Unlike conventional appliance-level disaggregation approaches, the proposed framework performs scenario-based classification, where each class represents a unique combination of simultaneously operating electrical appliances. The model is trained and evaluated on datasets consisting of operational scenarios involving two, three, and four electrical devices, with raw electrical signals transformed into kurtogram representations to emphasize salient signal characteristics. The experimental results demonstrate that a learning rate of 10^{-3} consistently outperforms 10^{-4}, achieving training accuracies of 98.04%, 99.95%, and 99.75%, along with precision values of 99.98%, 95.65%, and 97.10% for the respective scenarios. In contrast, the lower learning rate leads to noticeable performance degradation and higher residual training loss. These results confirm the robustness and effectiveness of the proposed NILI framework and highlight its potential for practical deployment in intelligent and sustainable energy management systems for future smart home environments.

Keywords-non-intrusive load identification; CNN–LSTM; residual block; squeeze-and-excitation; kurtogram

I. INTRODUCTION

The regulation of domestic power usage has drawn attention due to increasing energy expenses and energy efficiency prioritization. Household electrical appliance energy consumption data have been thoroughly studied to assist consumers in optimizing energy usage, minimizing expenditures, and promoting economic and environmental sustainability. Traditional energy monitoring technologies, including sensor-based systems that gather operational data, encounter obstacles associated with elevated prices, intricate installation, and maintenance complications. NILI, also known as Non-Intrusive Load Monitoring (NILM), has been widely studied as an effective approach for analyzing household energy consumption without deploying sensors on individual appliances [1]. As a result, research has transitioned to the development of detection and classification methodologies that utilize aggregate energy usage data [2, 3] alongside deep learning techniques [4]. These developments have lead to enhanced precision in energy classification and electrical appliance management, promoting novel solutions that improve the efficiency of energy analysis and consumption management.

Authors in [5] proposed an end-to-end machine learning architecture for NILM, which aims to identify the power consumption of individual appliances from the total household energy signal. Unlike conventional methods that rely on manual feature extraction and separate classification models, the proposed approach uses a unified Gated Recurrent Unit (GRU) network to learn directly from aggregated power data. This design simplifies the process, reduces computational complexity, and improves overall reliability. Using the REDD dataset for evaluation, the model demonstrated strong and consistent performance compared with traditional and deep learning-based NILM techniques, highlighting its potential for real-time energy monitoring and integration into modern smart metering systems. Similarly, authors in [6] proposed an Intelligent Home Energy Management System (IHEMS) integrating Vehicle-to-Home (V2H) technology with renewable energy sources such as solar power. The system enables electric vehicles to supply stored energy to households during peak demand, optimizing power usage through a Multi-Agent System (MAS). Each agent manages energy generation, storage, and consumption efficiently, adapting to weather and pricing conditions. The simulation results in Saudi Arabia show that the proposed model reduces energy costs, enhances sustainability, and improves overall household energy efficiency.

Authors in [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 deep learning frameworks, including ResNet50 [8], Bidirectional Long Short-Term Memory (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, the present study investigates the scalability of CNNs by enhancing their feature extraction capability through the expansion of convolutional layers, kernel configurations, and activation functions. In addition, a CNN-LSTM architecture integrated with residual connections is employed to promote feature reuse and mitigate information loss during deep feature propagation. The LSTM component is specifically designed to capture temporal dependencies in sequential energy consumption data, enabling more accurate modeling of electrical appliance usage patterns. Unlike conventional NILM approaches that focus on appliance-level power disaggregation, this study formulates the NILI task as a scenario-based classification problem, where each class represents a unique combination of simultaneously operating electrical devices. The proposed method is evaluated using energy consumption data from scenarios involving two, three, and four electrical appliances, with the raw signals processed through a kurtogram to emphasize discriminative frequency-domain features. This framework aims to advance NILI technology by improving classification efficiency and robustness, thereby enhancing its applicability to practical household energy management systems.

II. THEORETICAL BACKGROUND

A. Convolutional Neural Network

A CNN is a deep learning architecture developed for the extraction of critical features. It employs convolutional layers with filters for feature extraction, followed by an activation function to incorporate non-linearity. Furthermore, max-pooling is utilized to diminish dimensionality while retaining the most salient aspects of the data. The data undergo transformation into a vector and are subsequently processed through a classification layer, utilizing SoftMax for learning and classification purposes. This research employs CNN for its capacity to extract essential elements from intricate data, facilitating the analysis and categorization of energy consumption patterns of electrical devices, as demonstrated in:

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

where I represents an $M \times N$ image, K denotes the filter size for feature extraction, and $A(i, j)$ signifies the pixel value at coordinates (i, j).

The convolutional operation is performed by applying the filter $K(m, n)$ to $I(i, j)$ and conducting element-wise multiplication of the pixel values in the relevant picture region. The outcomes of these multiplications are subsequently aggregated to provide a feature map at coordinates (i, j). Thereafter, the input is converted into a vector and processed through the flatten layer and fully connected layer, as defined in:

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

where W represents the weight matrix, X is the input vector, and b denotes the bias term. The output processed by the SoftMax function normalizes the values into probability distributions for classification purposes.

B. Squeeze-and-Excitation-Residual Blocks

RBs [14] were created by Microsoft research to mitigate the vanishing gradient issue in deep neural networks, enabling models to learn intricate tasks more effectively. The main premise of RB is the implementation of skip links or shortcuts, which allow for direct data transfer from earlier layers to deeper layers, hence enhancing gradient propagation efficiency. This study includes RB as they maintain critical characteristics, alleviate gradient vanishing, and enhance network depth without sacrificing performance, as shown in:

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

where X represents the input to the RB, $F(x)$ denotes the learned transformation function, and y signifies the output of the block. As X traverses a convolutional layer, undergoes batch normalization, and applies an activation function, the resultant output F(x) is appended element-wise to the original input X over a skip connection. If the dimensions of $F(x)$ and X are incompatible, a convolution may be performed on X for dimensional conformity. This approach helps preserve essential information, alleviates the vanishing gradient issue, and facilitates the model's capacity to learn intricate functions efficiently.

Similarly, SE [15] is a CNN module that improves feature representation by channel-wise attention. It functions in three phases: squeeze reduces spatial dimensionality through global average pooling; excitation employs a two-layer fully connected network with ReLU and sigmoid activations to learn channel dependencies; and recalibration rescales feature maps by multiplying them with learned attention weights, enhancing significant features while diminishing the less relevant ones, as illustrated in:

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

where $X_C(i,j)$ denotes the pixel located at coordinates (i, j) within channel C, and H and W represent the spatial dimensions of the feature map derived from C. The compressed channel representation, Z_C , is obtained via channel compression. The resultant values are further processed via a learning mechanism to calculate the attention weights for each channel.

III. PROPOSED METHODOLOGY

A. Dataset

This work employs a dataset that documents the functioning of electrical equipment in a building [17], designed to monitor electrical loads without necessitating further installation at each usage point. The data were gathered in real time and encompass specifications of five categories of electrical devices: 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), following the data acquisition protocol and dataset introduced in [20]. Data recording was performed utilizing a programmable logic device, proficient in properly sampling operating signals, with each device sampling 1,000 data points (ON and OFF). The collected data were examined under three distinct scenarios:

- 2-device scenario: combinations of two electrical devices, comprising data12, data15, data25, data34, and data45.
- 3-device scenario: combinations of three electrical devices, comprising data124, data135, data145, data235, and data345.
- 4-device scenario: combinations of four electrical devices, comprising data1234, data1235, data1245, data1345, and data2345.

To make the data structure suitable for analysis, the behavioral patterns of each electrical appliance were converted to a corresponding kurtogram [18], as presented in Figure 1. The processed data were divided into 80% for training and 20% for testing to create and assess the model's performance in categorizing the energy consumption behavior of electrical devices.

(a)

(b)

(c)

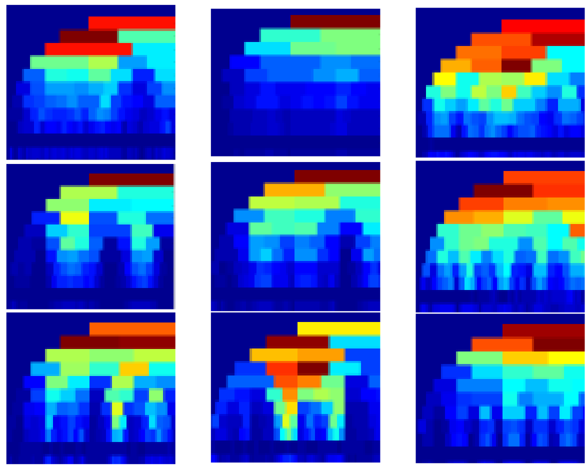


Fig. 1. Example kurtogram images from the electrical appliance dataset: (a) 2- devices, (b) 3- devices, (c) 4-devices.

B. Proposed Methodology

The present study modifies a CNN architecture [19] to derive deep features of electrical appliance performance attributes, highlighting the use of convolutional layers, RB, and SE-block. Figure 2 illustrates the overall architecture of the proposed CNN–LSTM-based scenario-based NILI framework. The input to the model consists of kurtogram images derived from aggregated electrical consumption signals, which provide a compact representation of non-stationary signal characteristics.

The feature extraction stage is composed of three convolutional blocks, each integrating residual connections and an SE-block. The RB connections enable effective feature reuse and alleviate the vanishing gradient problem, while the SE-blocks enhance channel-wise feature discrimination by adaptively recalibrating the importance of each feature map. As the depth of the network increases, the number of convolutional filters is progressively expanded to capture increasingly complex appliance interaction patterns.

Following the convolutional feature extraction, the resulting feature maps are flattened and passed through fully connected layers to integrate spatial features. These features are then fed into an LSTM layer with 128 units, which is employed to model the sequential dependencies inherent in electrical consumption patterns across time. The LSTM layer enables the network to capture temporal correlations between appliance operations, which are critical for distinguishing similar multi-device scenarios.

Finally, the output of the LSTM layer is connected to a SoftMax classification layer, where each output neuron corresponds to a predefined appliance operation scenario (e.g., data12, data145). The network is trained using categorical cross-entropy loss to perform multi-class scenario classification. This design allows the proposed architecture to effectively identify complex appliance usage scenarios from aggregated electrical signals.

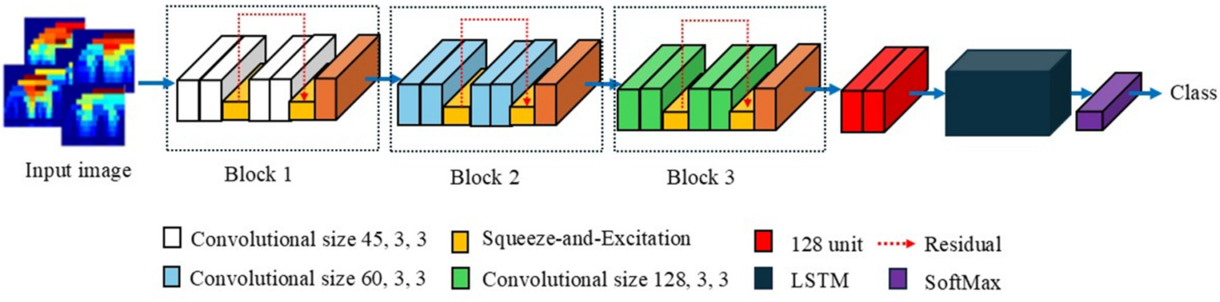


Fig. 2. Overview of the proposed CNN–LSTM architecture for scenario-based NILI.

C. *Evaluation*

For an in-depth examination, fundamental metrics, such as accuracy, precision, and loss, were employed, as defined in (5)-(7). A confusion matrix was utilized to evaluate classification accuracy and examine error patterns in recognizing the operational statuses of electrical equipment:

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

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

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{n}\sum_{c=1}^{c} y_{i,c}\, log\,(y_{i,c}) \quad (7)$$

IV. EXPERIMENTAL AND RESULTS

A. *Parameter of Training Model*

The studies were performed using a computer with an Intel Core i5-14400F CPU with 32 GB of RAM (5,600 MHz), and an NVIDIA GPU, RTX 5070 (12 GB of VRAM-6, 144 CUDA cores) to enhance network training efficiency.

TABLE I. TRAINING MODEL PARAMETER

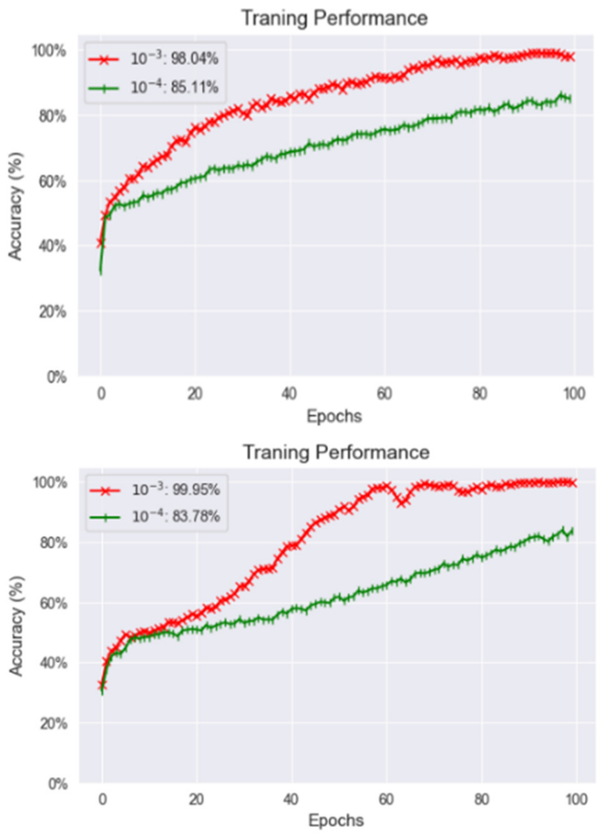
Parameter	Value
Image size	100×100×3
Learning rates	10^{-3}, 10^{-4}
Epochs	100
Batch size	128
Loss function	Categorical cross-entropy
Optimization	Adam
Evaluated utilizing	NumPy, TensorFlow

B. *Training Performance*

Figure 3 illustrates the training accuracy of the proposed CNN–LSTM model under different learning rates across integrated datasets comprising 2, 3, and 4 electrical appliances. For the 2-device scenario, a learning rate of 10^{-3} achieves a training accuracy of 98.04%, substantially outperforming the 85.11% obtained with a learning rate of 10^{-4}. Similarly, in the 3-device scenario, the model trained with a learning rate of 10^{-3} reaches a near-perfect accuracy of 99.95%, whereas the learning rate of 10^{-4} yields a considerably lower accuracy of 83.78%. In the most challenging 4-device scenario, the proposed model maintains a high training accuracy of 99.75% with a learning rate of 10^{-3}, while performance drops markedly to 76.95% when the learning rate is reduced to 10^{-4}.

(a)

(b)



(c)

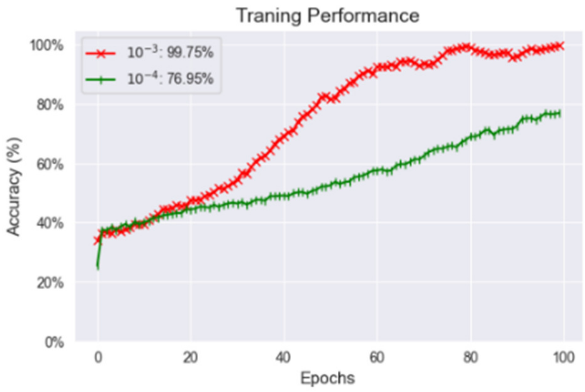


Fig. 3. Training accuracy of the proposed CNN–LSTM model under different learning rates: (a) 2-device scenario, (b) 3-device scenario, (c) 4-device scenario.

(a)

(b)

(c)

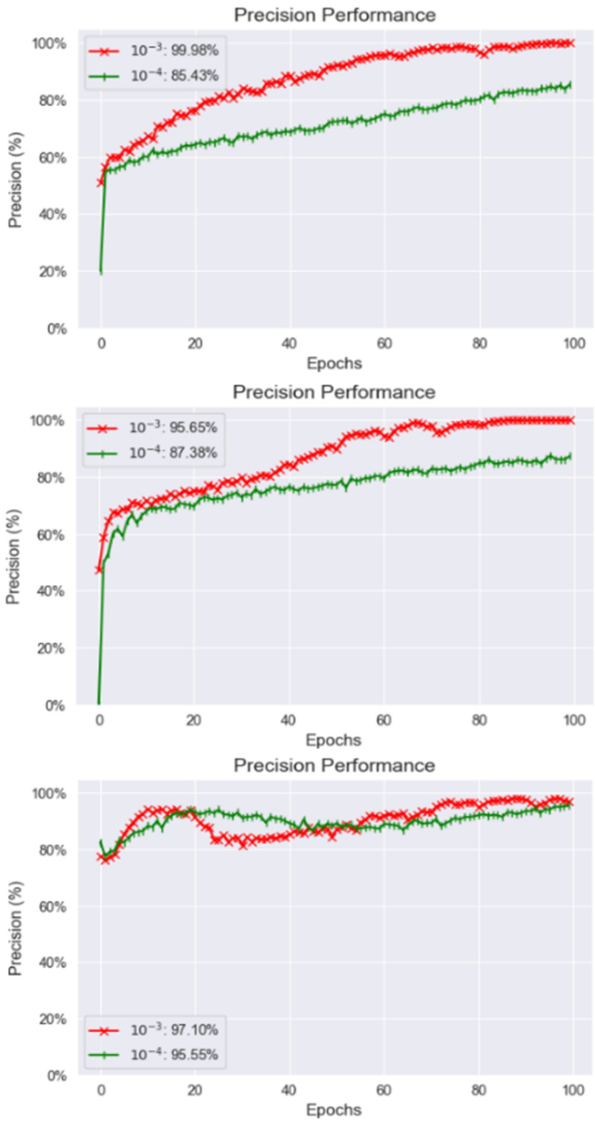


Fig. 4. Training precision of the proposed CNN–LSTM model under different learning rates: (a) 2-device scenario, (b) 3-device scenario, (c) 4-device scenario.

Figure 4 depicts the training precision of the proposed CNN–LSTM model under different learning rates across scenarios involving 2, 3, and 4 electrical appliances. In the 2-device scenario, the learning rate of 10^{-3} achieves a near-perfect precision of 99.98%, significantly outperforming the 85.43% obtained with a learning rate of 10^{-4}. For the 3-device scenario, precision reaches 95.65% when using a learning rate of 10^{-3}, compared to 87.38% under a learning rate of 10^{-4}. Similarly, in the 4-device scenario, the proposed model attains a precision of 97.10% with a learning rate of 10^{-3}, whereas the precision decreases to 95.55% when the learning rate is reduced to 10^{-4}.

Figure 5 displays the training loss curves of the proposed CNN–LSTM model under different learning rates for scenarios involving 2, 3, and 4 electrical appliances. Across all scenarios, the learning rate of 10^{-3} demonstrates a faster and more stable reduction in training loss, indicating a more efficient learning process and rapid convergence toward the optimal solution. In the 2-device scenario, the training loss using a learning rate of 10^{-3} decreases sharply and converges to a low final value of 0.0530, whereas the learning rate of 10^{-4} converges more slowly and stabilizes at a higher loss value of 0.3153, reflecting suboptimal learning behavior. For the 3-device scenario, the proposed model achieves its lowest loss value of 0.0031 when trained with a learning rate of 10^{-3}, representing the best performance among all evaluated cases. In contrast, the learning rate of 10^{-4} results in slow and incomplete convergence, with the loss remaining relatively high at 0.4542. A similar trend is observed in the 4-device scenario, where the learning rate of 10^{-3} consistently reduces the loss to 0.0189, while the learning rate of 10^{-4} converges slowly and remains at a significantly higher loss value of 0.6783.

C. Classification Performance

Figure 6 presents the confusion matrices of the proposed CNN–LSTM model for electrical device identification under the 2-device, 3-device, and 4-device scenarios. Overall, the results demonstrate that the proposed model achieves high classification accuracy across all scenarios, with most samples correctly classified along the main diagonal of each confusion matrix. In the 2-device scenario, the model exhibits strong discriminative capability, with minimal misclassification between appliance classes. This indicates that the proposed architecture can effectively capture distinctive electrical signatures when the number of simultaneously operating devices is limited. The diagonal dominance suggests stable learning and reliable device separation. For the 3-device scenario, although the classification task becomes more challenging due to increased overlap in electrical characteristics, the proposed model maintains a high level of identification performance. Most appliance classes are still accurately recognized, while minor misclassifications occur primarily between devices with similar operational patterns. This behavior reflects the increased complexity of multi-appliance interactions rather than deficiencies in the model structure. In the most complex 4-device scenario, the confusion matrix reveals a noticeable increase in inter-class confusion, particularly among appliances with overlapping power consumption profiles.

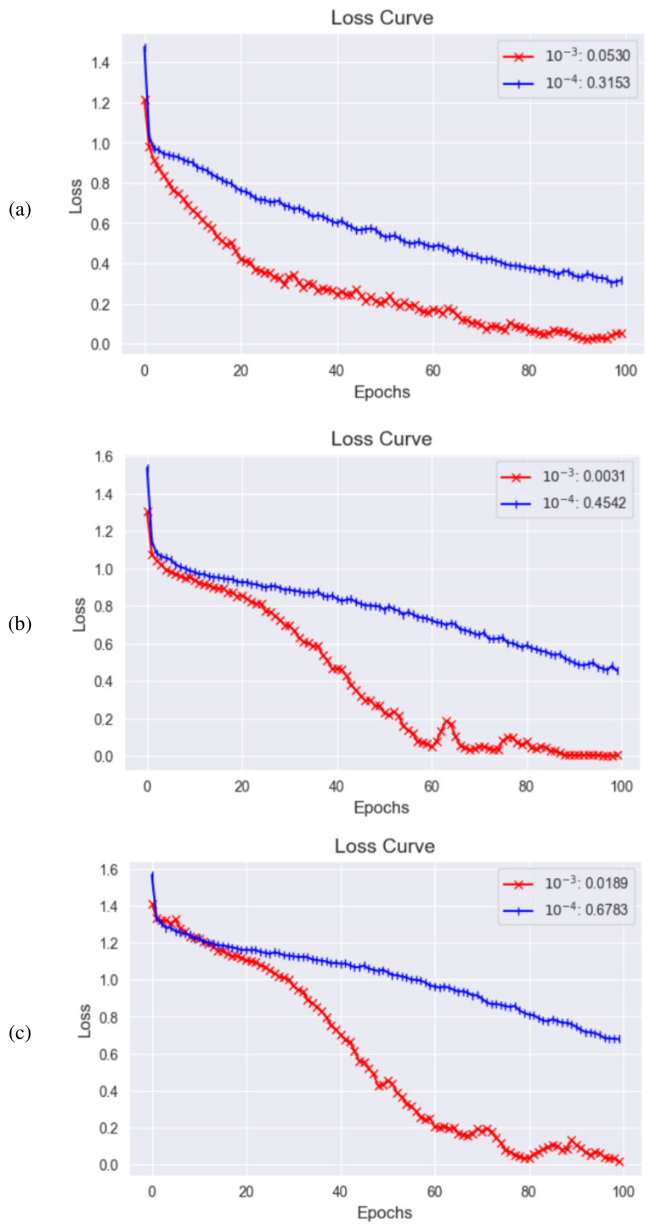


Fig. 5. Training loss of the proposed CNN–LSTM model under different learning rates: (a) 2-device scenario, (b) 3-device scenario, (c) 4-device scenario.

Nevertheless, the proposed CNN–LSTM model continues to demonstrate robust performance, preserving a strong diagonal distribution. This result highlights the effectiveness of integrating residual and SE blocks in enhancing feature representation and improving class separability under highly complex operating conditions.

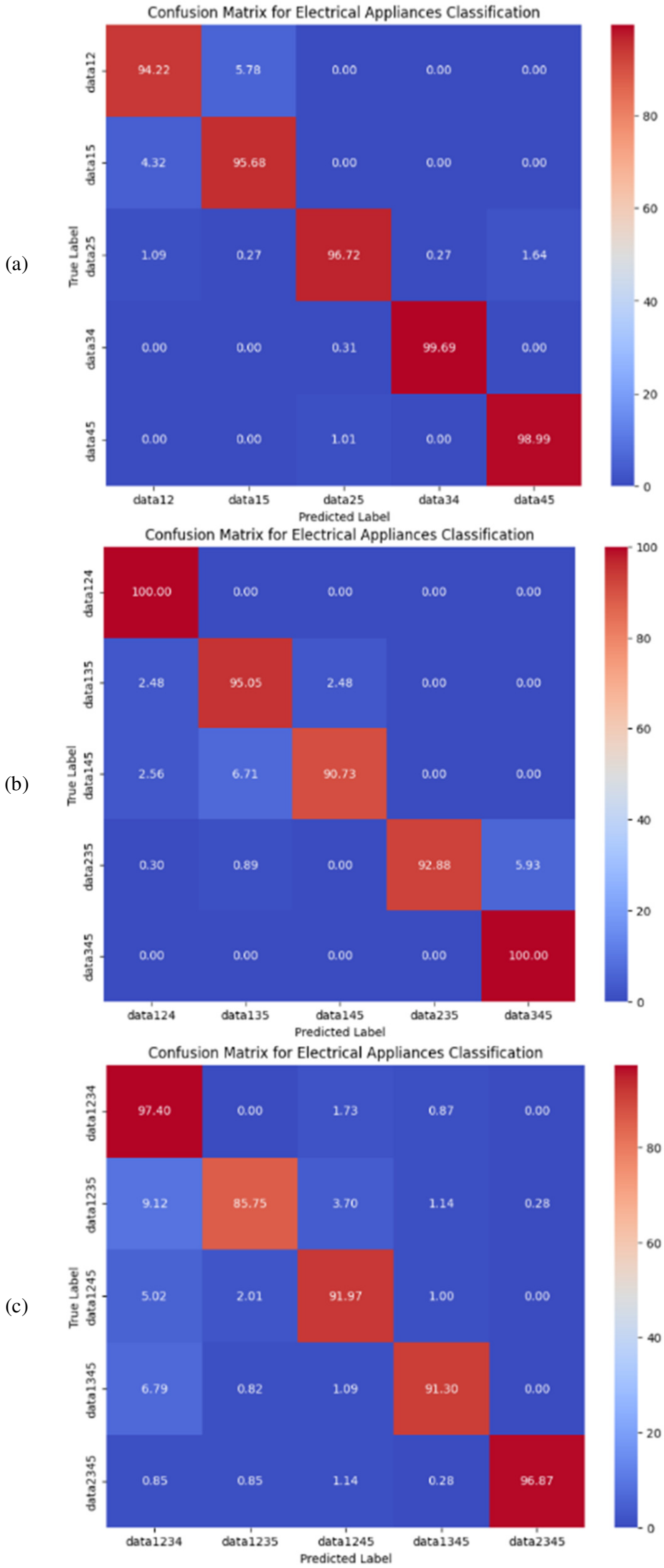


Fig. 6. Results of electrical devices identification: (a) 2-device scenario, (b) 3-device scenario, (c) 4-device scenario.

The gradual increase in misclassification with the number of devices further emphasizes the inherent difficulty of scenario-based NILI, while simultaneously validating the robustness and generalization capability of the proposed architecture.

D. Performance Evaluation

The performance results of the comparative models, presented in Table II, are adopted from their original studies, whereas accuracy, precision, and loss are consistently evaluated at the scenario level to ensure a fair and meaningful comparison with the proposed method.

TABLE II. PERFORMANCE COMPARISON WITH STATE-OF-THE-ART NILI MODELS

Model	Accuracy (%)	Precision (%)	Loss
CNN-based NILM [7]	97.00	-	-
GRU-based NILM [5]	91.22	-	-
SE-ResNet NILM [8]	96.24 and 96.40	-	-
Proposed CNN-SE-RB-LSTM	99.95	99.98	0.0031

V. DISCUSSION

A. Impact of Learning Rate on Model Performance

One of the most significant findings of this study is the pronounced influence of the learning rate on training stability and classification performance. Across all evaluated scenarios, a learning rate of 10^{-3} consistently outperforms 10^{-4} in terms of accuracy, precision, and convergence behavior. Specifically, the proposed model achieves high training accuracy exceeding 98% in all scenarios when using a learning rate of 10^{-3}, while a significant degradation in performance is observed under a learning rate of 10^{-4}. The loss analysis further supports this observation, where the learning rate of 10^{-3} leads to rapid and stable convergence to low loss values, even in the most complex 4-device scenario. In contrast, the learning rate of 10^{-4} results in slow convergence and significantly higher residual loss, indicating insufficient gradient updates during training. These results suggest that an inadequate learning rate restricts the model's ability to effectively optimize decision boundaries, particularly in scenario-based classification tasks where appliance signatures exhibit high similarity and overlap.

B. Effect of Complexity on Classification Performance

As the number of simultaneously operating electrical appliances increases from two to four, the classification task becomes inherently more challenging due to overlapping power consumption characteristics and correlated temporal patterns. This increased complexity is reflected in a gradual reduction in performance metrics, particularly under suboptimal training conditions. Despite this challenge, the proposed model maintains strong performance across all scenarios. In the 3-device and 4-device scenarios, high accuracy and precision values are still achieved when an appropriate learning rate is applied. This indicates that the proposed CNN–LSTM architecture is capable of capturing both local feature representations and long-term temporal dependencies, which are essential for distinguishing appliance operational patterns in multi-device environments. The observed performance degradation in higher-complexity scenarios should therefore be attributed to the intrinsic difficulty of scenario-based NILI rather than limitations of the proposed model itself.

C. Analysis of Confusion Matrix Results

The confusion matrix analysis provides further insights into the model's classification behavior. In the 2-device scenario, the confusion matrix exhibits strong diagonal dominance with minimal misclassification, confirming that the model can reliably distinguish between appliance classes when interference is limited. In the 3-device and 4-device scenarios, minor inter-class confusion emerges, primarily among appliances with similar electrical signatures. Nevertheless, most samples remain correctly classified, indicating robust generalization capability. This result highlights the effectiveness of incorporating residual connections to mitigate vanishing gradient issues and SE blocks to enhance channel-wise feature discrimination, particularly under complex operating conditions.

D. Architectural Advantages of the Proposed Model

Compared to conventional CNN–LSTM architectures, the integration of RBs facilitates deeper feature extraction without compromising training stability, while SE blocks dynamically recalibrate feature importance across channels. This architectural design enables the model to emphasize discriminative features and suppress redundant information, which is especially beneficial in scenario-based classification tasks involving multiple appliances. The consistent performance improvements observed across different scenarios and evaluation metrics validate the architectural choices and demonstrate the suitability of the proposed model for real-world NILI applications.

VI. CONCLUSION

This study presents a deep learning-based Non-Intrusive Load Identification (NILI) architecture aimed at improving energy consumption management through scenario-based classification. The proposed Convolutional Neural Network (CNN) and Long Short–Term Memory (LSTM)-based architecture, enhanced with Residual Blocks (RB) and Squeeze-and-Excitation (SE) blocks, effectively learns discriminative spatial features and long-term temporal dependencies from aggregated electrical signals. The experimental evaluations conducted on scenarios involving 2, 3, and 4 simultaneously operating appliances demonstrate that the proposed model achieves robust classification performance, even as scenario complexity increases. These results confirm the model's capability to capture complex device operation patterns and highlight its suitability for practical scenario-based NILI applications.

Beyond the scope of this study, several promising research directions can be explored to further extend the proposed architecture. Future work will investigate adaptive learning rate scheduling and early stopping strategies to improve training stability and generalization, particularly in more complex multi-appliance scenarios. Additionally, extending the current scenario-based formulation toward hybrid frameworks [13] that integrate scenario classification with appliance-level disaggregation [16] may enhance scalability and applicability in real-world energy systems. The incorporation of additional signal representations or multimodal inputs, such as voltage–current trajectories and contextual sensor data, also represents a valuable direction for improving discrimination capability. Furthermore, future efforts will focus on deploying the proposed model on embedded and edge-computing platforms to enable real-time intelligent energy management in smart homes and intelligent building environments.

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