EAI Endorsed Transactions
on Energy Web
Research Article EAI.EU

Deep Learning Model for Feature Extraction and Anomaly Recognition in High-Dimensional Energy Metering Data

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Abstract

Introduction: The rapid expansion of energy networks has significantly increased energy consumption, resulting in higher electricity costs. Abnormal energy usage in buildings and industries, often caused by system malfunctions, leads to substantial energy waste. Detecting such anomalies is essential for cost control and efficient energy management.
Objectives: This study aims to develop a deep learning-based method to detect anomalies in high-dimensional energy metering data, overcoming the limitations of existing techniques that struggle with data complexity and lack effective contextual analysis.
Methods: High-dimensional metering data from a city energy provider is processed using a Convolutional Autoencoder (CAE) to extract deep features and reduce dimensionality. These features are then fed into a Cascaded Long Short-Term Memory (CLSTM) network, which identifies anomalous patterns in the data.
Results: The cascaded CLSTM model effectively detects anomalies in the energy consumption data by accurately predicting deviations from normal patterns.
Conclusion: The proposed CAE-CLSTM approach enhances anomaly detection in complex energy datasets, enabling more effective monitoring and reducing unnecessary energy waste and costs.

Keywords: energy consumption, deep learning-based approach, high dimensional energy metering data

Received on 20 May 2025, accepted on 07 July 2025, published on 20 August 2025

doi: 10.4108/ew.9363

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Introduction

High-Dimensional Energy Metering Data

For scientific and technological development, energy is considered an essential component. The energy demand is high due to technological and social development. Residential and commercial buildings can consume a significant amount of energy. The dimension of the metering data increases due to frequent energy utilisation. The energy meters installed in industries and households measure electricity consumption over a short period [1]. The metering data available in higher dimensions is referred to as high-dimensional metering data [3]. In data transmission, managing high-dimensional metering data is a complex task. This high-dimensional metering data resulted from the extensive development of smart metering devices [5]. The smart meter system is used to collect data regarding electricity consumption in large-scale buildings. Anomaly detection in large-scale smart meter data raises key privacy and security concerns. It can reveal sensitive user behaviour, posing risks of data misuse or breaches. Misclassification may lead to false alarms or invasive monitoring, and the models themselves can be vulnerable to cyberattacks. To ensure responsible use, strong data protection, transparency, and ethical oversight are essential. The quality of the power and the electricity consumption of the user can be greatly affected by the low-voltage distribution system [8]. The metering system is installed on the consumer side to gather a huge amount of electricity data. The smart metering system has monitored energy usage. The data management system receives high-dimensional metering data for the analysis process. A huge quantity of metering data is generated by the smart meters deployed in various industries, household organisations, and other settings. Moreover, the high-dimensional metering data is heterogeneous. High-dimensional energy metering data is highly heterogeneous due to varying time intervals, diverse sources, different measurement types, and user behaviour. This complexity presents challenges in preprocessing, including handling noise, redundancy, missing data, and the curse of dimensionality. Anomaly detection is further complicated by unclear definitions of abnormal behaviour and sparsely labelled data. Traditional methods struggle in this context, while deep learning techniques, such as CAE and CLSTM networks, offer effective solutions. The data developed by the smart meters are available in high dimensions. Smart meters generate complex, high-dimensional data due to their ability to record information frequently across multiple measurement channels. This data includes various electrical parameters such as voltage, power, and frequency, as well as temporal and behavioural usage patterns. The inclusion of metadata, such as time, location, and device context, adds further complexity. To analyse this data effectively, particularly for identifying unusual consumption patterns, deep learning methods are employed. Convolutional autoencoders help reduce the dimensionality by removing irrelevant information, while cascaded LSTM networks analyze the refined data to detect anomalies over time. Additionally, the real-time analysis process is facilitated by high-dimensional metering data [7]. The high-dimensional metering data falls under the category of big data, consisting of several electricity observations [22]. The energy efficiency of the industries and residential sector is improved through an energy metering system. The energy supplier receives information on energy consumption through the energy metering system [4]. The metering system is located on the consumer side to measure data consumed by the corresponding user. The control capabilities, energy measurement, and monitoring activity of the energy metering system are high. High-dimensional metering data is generated due to the extensive deployment of smart meters [7]. By using the multi-scale fusion neural network technique from Valivarthi and Hemnath (2018) [36], our proposed work builds upon their approach by utilizing layered feature extraction to high-dimensional energy metering data, which improves anomaly recognition and enhance model robustness in complex data environments.

Energy consumption data across residential, commercial, and industrial settings presents distinct patterns and challenges. Residential data is generally low and routine, but it varies due to lifestyle changes, making anomaly detection challenging. Commercial settings have structured energy use but face issues with overlapping loads and large data volumes. Industrial data is the most complex and voluminous, with noise and variability complicating anomaly detection. Common challenges across all sectors include high-dimensional data, difficulty in distinguishing between normal and abnormal use, and the need for real-time, accurate analysis. Advanced deep learning models, such as CAE and CLSTM, are essential for effective feature extraction and anomaly recognition.

Anomaly-based Challenges on High-Dimensional Energy Metering Data

Higher electricity consumption and energy wastage occur due to anomalous power consumption activities. Effective electricity utilisation is achieved by identifying abnormal power usage. The wastage of energy in the building is prevented by identifying the abnormal energy consumption [1]. In the current research field, identifying anomalous power consumption is a challenging process because the distinction between anomalous and normal energy is not clearly defined in any existing research work. This makes the anomaly detection process a challenging task. Moreover, the boundary between abnormal and normal energy is not defined. Moreover, the existing techniques do not handle the unified metrics of high-dimensional metering data. Due to the factors above, anomaly detection in high-dimensional metering data is a challenging process. The minimum quantity of the ground truth dataset is the major obstacle to developing the anomaly detection process. Moreover, the labelling process for normal and abnormal energy data is not proposed in the existing studies. Energy metering data can be categorised into three types: point, contextual, and collective. Point anomalies differ significantly from typical values, while contextual anomalies are abnormal within a specific context. Collective anomalies form unusual patterns over time, potentially indicating energy theft or system inefficiency. These anomalies are critical as they often reflect long-term operational issues or fraudulent activities. A deep learning approach combining CAE and CLSTM networks is effective in detecting these complex anomaly types in high-dimensional energy data. Contextual information helps differentiate normal usage from abnormal usage, improving detection accuracy and reducing false positives. The existing technique does not automatically identify the anomalies in the high-dimensional metering data. Furthermore, the energy consumption activity is not effectively classified by the traditional model, as it necessitates a huge number of parameters. The researcher presents a neural network technique to detect anomalies and then evaluates its performance in comparison to other techniques. Furthermore, a collection of specifications is chosen to evaluate the effectiveness of the method. High-dimensional metering data analysis raises two significant difficulties. Euclidean distance is ineffective for anomaly detection in high-dimensional energy data because it loses discriminative power, is influenced by irrelevant and sparse features, and becomes computationally expensive. It also fails to capture complex patterns and temporal dependencies. To overcome these limitations, deep learning models such as Cascaded LSTMs and Convolutional Autoencoders are used to extract meaningful features and accurately detect anomalies. The first problem arises because of the Euclidean distance. It is used to gauge the similarity between two identical instances of data in low-dimensional space, but it provides poor results in high-dimensional spaces. Some of the classical anomaly detection techniques become less successful as dimensionality increases. When analysing high-dimensional metering data, the data takes on a sparse nature, and noise effects obscure the actual features in the high-dimensional metering data. Additionally, the quantity of processes required for the analysis and processing of these data increases rapidly, and the expense associated with these computations also rises exponentially. Certain difficulties arise when identifying anomalies in high-dimensional data, which are discussed in the following points. The attributes irrelevant to anomalous data usually appear in high-dimensional metering data. These unnecessary attributes create an impact on high-dimensional metering data anomaly detection. Irrelevant features in high-dimensional energy metering data introduce noise, increase computational costs, and increase the risk of overfitting, thereby weakening anomaly detection performance. The proposed CAE-CLSTM model addresses this by using a Convolutional Autoencoder to extract essential features and reduce dimensionality, followed by a Cascaded LSTM network that further refines the data for accurate anomaly detection. This approach enhances signal clarity and detection accuracy, outperforming traditional methods like PCA and AE across key performance metrics. Furthermore, the utilization of classical anomaly detection techniques relies on distance, volume, and other factors, which increase the complexity of the anomaly detection process [3]. Anomaly detection in high-dimensional energy metering data is challenging due to the large number of features, data heterogeneity, sparsity, and noise. The absence of labelled data and clear boundaries between normal and abnormal behaviour further complicates detection. Temporal dependencies in the data necessitate models that can capture sequential patterns, while redundant features further complicate the analysis. Additionally, high computational costs make real-time analysis difficult. These challenges highlight the need for advanced deep learning techniques, such as Cascaded LSTM and Convolutional Autoencoder networks, to effectively extract features and detect anomalies.

All the components of the data are often employed in the process of anomaly identification using conventional methods; however, these data consist of numerous insignificant features, which can affect the results of anomalous data detection. Moreover, redundant features in the high dimensional metering data could lower the success rate of anomaly detection. There are several techniques available to identify anomalies in high-dimensional metering data, including linear frameworks, nearest-neighbour-based approaches, and statistical models. Nevertheless, implementing the detection of anomalies on high-dimensional metering data is very expensive, and their performance in identifying the anomaly effect of high-dimensional data is not very good. Consequently, these methods are not directly applied to anomaly detection on high-dimensional metering data. High-dimensional energy metering data is generated by smart meters and includes numerous features collected at high frequency across many locations, making it complex, large-scale, and often noisy. This complexity poses challenges for anomaly detection, as traditional methods struggle with irrelevant features, sparse data, and computational demands. Deep learning approaches, such as Convolutional Autoencoders for feature extraction and Cascaded LSTM networks for temporal analysis, provide effective solutions by capturing intricate patterns and enhancing anomaly detection accuracy in these datasets. The efficiency and detection impact of anomaly detection can be greatly increased by eliminating unnecessary features. The complicated interaction between characteristics makes feature extraction a challenging process [3]. High-dimensional metering data analysis technologies and electricity usage data acquired by smart meters are used to characterise consumers' electricity consumption. However, in the anomalous usage of electricity, the system is unable to manage the user energy data. In marketing and grid companies, the timely identification of anomalous activity is necessary [8].

Importance of Deep Learning in Anomaly Recognition

The fundamental goal of detecting anomalies in industrial energy applications is to identify irregularities in energy usage. Detecting anomalies in energy consumption helps improve efficiency and reduce costs by identifying irregular usage caused by theft, faults, or inefficiencies. Early detection prevents unnecessary expenses, enables data-driven energy planning and supports predictive maintenance. Advanced models, such as CAE-CLSTM, enhance this process by accurately identifying anomalies in complex energy data, leading to improved monitoring and reduced energy waste. The abnormalities in energy usage must be found to perform maintenance or shut down systems [13]. Basani et al. (2024) [31] proposed a Deep Multi-Scale Fusion Neural Network that integrates data fusion with multi-scale feature extraction to improve fault diagnosis in IoT systems. Our proposed work adopts this technique to enhance feature extraction and anomaly recognition in high-dimensional energy metering data. Deep learning approaches automate the entire anomaly detection pipeline; additionally, they are designed to learn the representation for anomaly detection. At the same time, conventional approaches lack these qualities. Specifically, deep learning techniques significantly diminish the requirement for labelled data. To increase the recall rate of the anomaly detection process, deep learning techniques are necessary. In the context of anomaly detection in high-dimensional data, deep learning techniques, including black-box models, consolidate anomaly detection and interpretation into a single structure, leading to the effective interpretation of anomalies identified in high-dimensional metering data. Intricate patterns and relations can be learned from high-dimensional metering data using deep learning techniques.

Furthermore, the deep learning methods acquire unified representations of high-dimensional metering data. This enables the deep models to identify both the complex anomalies and the differences between the usual and abnormal metering data. Although existing strategies do not handle those complicated data, they are usually less adaptive and much weaker than deep learning techniques [23].

In recent years, interest in deep learning has increased significantly. Without assuming underlying patterns in the data, deep learning techniques discover the complex structure present in the high-dimensional metering data. For example, the Stationary Wavelet Transform (SWT) combined with ensemble Long Short-Term Memory (LSTM) neural networks enables the identification of long-term patterns in high-dimensional data to forecast energy consumption. The anomaly detection system utilises deep learning to analyse high-dimensional energy data by combining three key techniques: hierarchical feature learning through a CAE to extract and compress important features, temporal dependency modelling using a CLSTM network to capture patterns over time, and nonlinear mapping capabilities to detect complex relationships within the data. The test findings demonstrated that the proposed deep-learning approach outperforms traditional algorithms. The deep learning-based anomaly detection techniques provide an outline of the features in high-dimensional data. These models establish the relationships between variables and provide the temporal context, as well as identify abnormalities in high-dimensional data [24]. Our proposed deep learning model for anomaly recognition in energy metering data leverages the VAE-GAN with a CNN-based feature extraction strategy, as emphasised by Gudivaka et al. (2024) [29], to enhance high-dimensional pattern learning, improve anomaly detection accuracy, and effectively handle imbalanced data in smart energy systems. Numerous deep learning and statistical methods are adopted for the anomaly detection process in high-dimensional metering data, as the generalizability of this model is high. However, these techniques are not performed well due to the computing delay and lower recognition rate [11].

Contribution

The crucial contributions of the proposed deep learning-based anomaly detection are listed below.

- To implement an anomaly recognition model in High-Dimensional Energy Metering Data using deep learning techniques.
- To perform an efficient feature extraction process with the utilization of a convolutional autoencoder for enhancing the performance of anomaly recognition.
- To develop a deep learning model by cascading the LSTM network for analyzing the deep features of energy metering data to find anomalies in it.
- To analyze the model performance on anomaly recognition by comparing it with the existing techniques based on various measures.

Review

The anomalous energy consumption in the building and industrial sectors can be identified to enhance the energy efficiency of buildings and industries. The pattern of anomalies in high-dimensional energy metering data is analysed using deep learning-based anomaly detection techniques [15]. Several existing techniques for feature extraction and anomaly detection in high-dimensional metering data are described as follows.

Chiosa *et al*. [2] have proposed an Anomaly Detection and Diagnosis (ADD) approach for identifying anomalous behaviour in meter-level building data. This model could identify the anomalous pattern of the data. Hopf *et al*. [4] have explored a supervised machine-learning model for extracting features from smart electricity meter data. It was used to lower the dimension of the large-scale metering data. Chahine *et al*. [9] have suggested a feature extraction approach for the load disaggregation process. The obtained features could be used to form a database, which was then used for the load classification process. Yuan and Jia [11] have developed a deep learning technique for the distributed anomaly detection process.

The stacked sparse autoencoder retrieved the features from the smart meter network data. Finally, the anomaly in the data was identified by the softmax. Liu *et al*. [12] have developed a data mining-based framework for retrieving the electronic load pattern in the data. This model could identify the anomalous load profiles in the data. It performed both pattern examination and anomaly detection on the electricity data. Hock *et al*. [14] have recommended a multidimensional anomaly detection approach for the electricity data. The outliers were created as a result of the electricity theft detection process. Xu and Chen [16] have recommended a recurrent neural network-based anomaly detection process on the building's electricity consumption data. It could effectively determine the abnormal energy consumption in the building. Himeur *et al*. [17] have suggested rule-based techniques for detecting anomalies in data by extracting micro-moment features. This feature extraction process is used for performing anomaly detection on high-dimensional energy consumption data. Fan *et al*. [19] have proposed an autoencoder structure for detecting anomalies in energy metering data. The autoencoder could effectively learn the features in the metering data using its unique feature learning mechanism. Granell *et al*. [20] have recommended a system for retrieving the features in the electricity load profile. Here, the load profile could be effectively represented because it simplified the features in the electricity load profile.

In the power system, metering data from the electric energy meter is considered a crucial process, and electricity usage can be measured by the energy meters. The measurement of high-dimensional metering data is abnormal due to the occurrence of manual errors [26]. The conventional techniques for detecting anomalies in high-dimensional smart metering data are quite challenging. The high-dimensional smart metering data consists of noise and distinct patterns that the existing techniques cannot handle. During the training process, existing techniques automatically shrink, which affects the quality of the anomaly detection process [27]. Therefore, the cascaded LSTM structure is suggested for performing anomaly detection on high-dimensional metering data, as it fixes the threshold value to analyse the pattern in the data, allowing anomalies to be effectively identified.

Methodology

Description of the proposed model

Deep learning-based anomaly detection techniques are developed to identify anomalous activity in high-dimensional energy metering data, thereby preventing higher electricity consumption by detecting anomalous energy consumption. Moreover, the efficient utilisation of energy is also achieved through the proposed anomaly detection model. In this process, high-dimensional energy metering data is utilised for anomaly detection. Deep learning models, such as CAEs and LSTM networks, are well-suited for detecting anomalies in high-dimensional energy metering data. CAEs extract meaningful spatial features by reducing data dimensionality and noise, while LSTMs capture temporal patterns and long-term dependencies. The combination of these models enables accurate, scalable anomaly detection by effectively handling complex, noisy, and time-dependent data. The high-dimensional energy metering data consists of some unwanted information, and this unnecessary data must be removed from the high-dimensional energy metering data. For retrieving deep features from high-dimensional data, a CAE is used. The CAE structure is composed of a combination of AE and CNN. The characteristics of high-dimensional energy metering data are considered by the CAE [5]. Additionally, the CAE model produces a minimum reconstruction error when compressing the dimensional space into lower-dimensional data.

Finally, the deep features extracted using the CAE are passed to the CLSTM (Cascaded Long Short-Term Memory). The cascade LSTM structure is formed by continuously cascading the standard LSTM structure. Here, the output produced by the first LSTM structure is passed to the next LSTM to get the outcome. Here, three LSTM structures are continuously cascaded in the CLSTM structure. The initial LSTM structure takes a huge amount of deep features extracted by the CAE. It processes a huge amount of data, so its accuracy level in the anomaly detection process is slightly low. In the second LSTM structure, the amount of data is considerably reduced, as it only considers the features that the first LSTM structure has identified. The final LSTM in the cascaded network determines the presence of an anomaly in the high dimensional metering data. Finally, the results of the developed model are compared with those of existing techniques to verify the reliability of the proposed anomaly detection model. Feature extraction is essential for effective anomaly detection in high-dimensional energy metering data. It reduces complexity by eliminating noise and redundant information, making data easier to process. Techniques like CAE compress data with minimal loss, improving signal clarity and enabling models like CLSTM to detect anomalies more accurately. This approach not only improves detection accuracy but also addresses the challenges of the "curse of dimensionality," making real-time, scalable anomaly detection feasible and efficient. The diagrammatic representation of deep learning-based feature extraction and anomaly detection in high-dimensional metering data is specified in Figure 1.

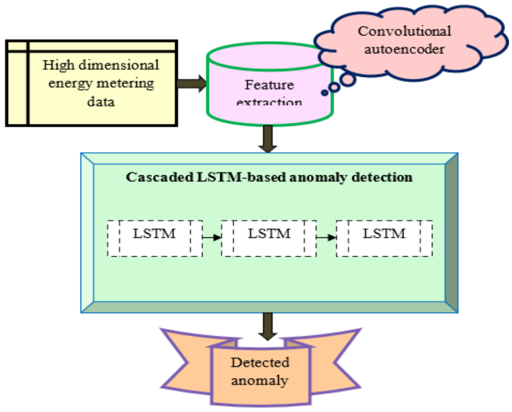


Figure 1: Diagrammatic representation of deep learning-based anomaly detection

Energy Metering Data Collection

The total amount of energy consumed in a particular time interval is identified by the energy meter. The metering systems measure the power consumption in households, as well as in other industries, and provide the corresponding readings for the power consumption [25]. The distribution and the generation of electricity to the user are managed by the energy meter. The consumer can be adequately aware of their electricity consumption, as the energy meter effectively records electricity consumption in the form of data [10]. The energy metering data collection is the first step in the anomaly detection process. For performing anomaly detection on high-dimensional metering data, there is no publicly accessible dataset. Here, the data from several sources are integrated to perform the anomaly detection process. Numerous laws are available for protecting high-dimensional metering data at the neighbourhood level [6]. The energy provider in the city provides high-dimensional energy metering data for the anomaly detection process [6].

Deep Feature Extraction with Convolutional Autoencoder

The obtained high-dimensional metering data consists of a high-dimensional vector, making it difficult to perform anomaly detection on the high-dimensional metering data. In this case, the CAE is suggested to retrieve the deep features from the high-dimensional metering data. Therefore, the dimension of the metering data is greatly minimized [5]. The CAE can consider the characteristics of high-dimensional metering data. The high-dimensional vector of energy metering data is converted into a lower-dimensional vector using the CAE, and it produces a very small amount of reconstruction error during the dimension reduction process [5]. Cascading three LSTM layers in the CLSTM architecture enhances its ability to process high-dimensional energy metering data and detect anomalies with greater accuracy. The first LSTM layer handles a large amount of raw data, albeit with lower accuracy, while the second layer refines the data flagged by the first, thereby improving precision. The third layer fine-tunes the analysis, further increasing accuracy. This cascading approach helps manage complex, noisy data by progressively reducing its volume, allowing the model to focus on relevant patterns and improving anomaly detection. The use of three layers strikes a balance between data refinement and complexity, ensuring effective anomaly detection in high-dimensional data.

Convolutional Autoencoder [5]: The CNN and the AE are connected to form the CAE. The encoder and decoder parts are available in the AE, as it is a type of artificial neural network. The input data y is passed to the encoder of the AE via the multiple fully connected layers. As a result of this transformation process, the input data y is converted into an encoded vector a. The decoder of the CAE gives the reconstruction y' from the encoded vector a. The autoencoder's encoding and decoding action is described in Eq. (1).

$$a = \gamma\left(X_{encoder}y + c_{encoder}\right) \qquad (1)$$

Here, the input data is represented as $y \in \varepsilon^{e}$, and the encoded data is represented as $y \in \varepsilon^{e'}$, the nonlinear activation function is represented as $\gamma : S^{e'} \rightarrow S^{e'}$, the weight of the hidden layer is represented as $X_{encoder} \in \varepsilon^{e' \times e}$. The bias of the hidden layer is expressed as $c_{encoder} \in \varepsilon^{e' \times e}$. The outcome from the autoencoder is represented in Eq. (2).

$$y' = \gamma\left(X_{decoder} y + c_{decoder}\right) \qquad (2)$$

The value of $X_{decoder}$ and $X^{T}_{decoder}$ is the same if the weight of the autoencoder is tangled together. The parameters of the AE are partially compressed because of the tangling action. The tied weight and multiple hidden layers are available in the AE. By utilising the backpropagation algorithm, the weight value is updated, thereby eliminating the reconstruction error $\| y - y' \|^2$ in the AE. The CAE serves as an essential component in processing high-dimensional energy metering data by simultaneously extracting deep, meaningful features and reducing data dimensionality. It combines Convolutional Neural Networks with Autoencoders to highlight critical patterns, eliminate noise, and retain key information while minimizing reconstruction loss. This compact, informative representation is then passed to the Cascaded LSTM for effective anomaly detection. The CNN in the CAE is used to obtain the nonlinear transformation in the CAE. The convolutional and pooling layers are two distinct layers of the CNN. Between the learnable filter and the input matrix, the convolution operation is performed to generate the feature map in the convolutional layer. For the matrix $S \; D$, the convolutional operator is identified using Eq. (3).

$$S(j,k) \bullet D(j,k) = \sum_{s1=-\infty}^{-\infty} \sum_{s2=-\infty}^{\infty} S(j - s1, k - s2) D(s1, s2) \qquad (3)$$

Here, the row and column indices are represented as j r and c, k respectively. In the CAE, the filter and the feature map are substituted for each other, not instead of $S \; D$. For the layer m , the l^{th} feature map and filter are represented as $G^{l}_{m} \in \varepsilon^{x_m \times i_m}$, and $X^{l}_{l'} \in \varepsilon^{x'_m \times i'_m}$ respectively. The prior layer $G^{l'}_{m}$ is convoluted with the feature map l'. In the layer m , the width and height of the filter are represented a x'_m nd i'_m corresponded accordingly. The value G^{l}_{m} is identified using Eq. (4).

$$G^{l}_{m}(j,k) = \gamma\left(\sum_{l'=1}^{e_{m-1}} X^{l}_{l'}(j,k) \bullet G^{l'}_{m-1}(j,k) + c_l\right) \qquad (4)$$

Thus, the activation function is signified as γ . The CNN learns the features in the convolutional layers. The value in the predetermined spatial unit is retrieved for minimizing the height of the pooling layer. The decoder of the CAE requires a dimensionality expansion process, which includes an unpooling layer and an inverse convolutional layer. The working process of both layers is opposite to that of the pooling and convolutional layers. Based on the feature map, the filter values are reset using the inverse convolution layer. In the pooling layer, the discarded location information is restored by the unpooling layer [5]. The structural view of the CAE is signified in Figure 2.

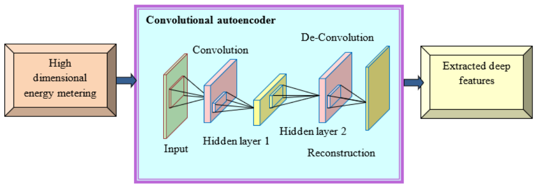


Figure 2: Structural view of the convolutional autoencoder

Anomaly Recognition with Cascaded LSTM

The cascaded LSTM is used to identify anomalies in high-dimensional metering data. The cascaded structure consists of two or more LSTMs and can be used to maintain the nonlinear relationship between high-dimensional metering data, yielding accurate detection results. The cascaded structure is formed by connecting the three LSTM structures. The initial structure can have the ability to process the huge dimensional data, but it gives less accurate results. The first LSTM can flag the data and then be processed by the second LSTM, yielding an outcome that is comparatively better than that of the first LSTM structure. The final LSTM structure in the LSTM can predict the presence of an anomaly in high-dimensional metering data. The cascaded LSTM (CLSTM) architecture enhances anomaly detection in high-dimensional energy data through a three-stage refinement process. First, a convolutional autoencoder extracts deep features from the raw data. The first LSTM processes all features and flags suspicious ones based on prediction errors. The second LSTM analyzes only the flagged features for more precise assessment. Finally, the third LSTM evaluates refined anomaly scores to make the final decision regarding anomaly detection. This layered approach improves accuracy by progressively narrowing the focus from general patterns to specific anomalies. The cascaded structure is primarily adopted to process high-dimensional metering data because it consists of three LSTM structures, which provide accurate results [21].

Cascaded LSTM: The cascaded LSTM consists of an additional LSTM structure; here, the output of one structure is given as the input of the subsequent LSTM. The basic LSTM model is continuously cascaded to form the cascaded LTSM. Here, the states of the memory cell in the cascaded network are controlled using the standard LSTM. Every individual block of the cascaded LSTM detects the anomalies in the data. The learning capacity of the cascading LSTM is superior to that of the standard model. The cascaded LSTM structure can eliminate feature redundancy.

Cascading LSTM layers are a method used to refine temporal representations and isolate anomalous patterns with higher accuracy. Each layer plays a distinct role in a hierarchical refinement process. The first layer captures broad temporal dependencies and flags potentially anomalous segments within high-dimensional features, ensuring significant patterns are not missed. The second layer operates on a reduced and filtered feature space, detecting subtle temporal relationships and eliminating false positives. The third layer makes a definitive prediction regarding the presence of anomalies by evaluating residual uncertainties and consolidating refined information from earlier layers. This layered processing approach is effective in handling noisy and complex high-dimensional data. Unlike single-layer or parallel architectures, cascading distributes learning across multiple stages, mitigating the vanishing gradient problem and enhancing model stability and generalization.

Cascading Long Short-Term Memory (CLSTM) networks enhance traditional LSTMs by stacking multiple layers that progressively refine and process high-dimensional data, improving anomaly detection. The first layer flags relevant features, the second refines them, and the final layer detects anomalies. This structure efficiently handles complex data, reduces redundancy, and captures nonlinear relationships. CLSTMs outperform traditional models, such as LSTM-AE, in terms of accuracy and performance, making them ideal for tasks like energy consumption monitoring, where detecting subtle anomalies is crucial.

Convolutional Autoencoders offer significant advantages over traditional methods, such as LDA and PCA, for feature extraction in high-dimensional energy metering data. They effectively capture nonlinear and hierarchical patterns, are robust to noise, and preserve important information with lower reconstruction errors. CAEs also enhance the performance of downstream models, such as cascaded LSTMs, and support automated, scalable feature learning, making them more suitable for complex energy datasets.

Long Short-Term Memory (LSTM) [18]: The LSTM model falls under the category of recurrent neural networks. The LSTM structure is trained using backpropagation through time. This training process greatly fathoms the vanishing gradient issues. Several memory blocks are available in the LSTM, and the layers are used to connect these memory blocks. The output and the state of the block are used to manage the gates available in each block. In the LSTM unit, three gates are situated. The forget gate determines the flow of information towards the LSTM block. The memory state is updated by the input value, which is determined by the input gate. The output gate decides the flow of output from the memory gate. During the training process, the weights present in the gate are precisely learned. The sigmoid layer is the initial step in the LSTM, and another name for this layer is the forget gate. The terms i_{u-1} y_u are the input values of the LSTM. The bias vector is represented as c, and the attribute indices are represented as X. The forget gate of the LSTM model is elucidated in Eq. (5).

$$g_u = \mathrm{K}\left(X_g \bullet [i_{u-1}\ y_u] + c_g\right) \quad (5)$$

The value to be upgraded can be determined by the input gate, as represented in Eq. (6).

$$j_u = \mathrm{K}\left(X_j \bullet [i_{u-1}\ y_u] + c_j\right) \quad (6)$$

The new candidate vector value $\hat{D}_u$ is developed by the $\tan h$ layer and is defined in Eq. (7).

$$\hat{D}_u = \tan h\left(X_D \bullet [i_{u-1}, y_u] + c_D\right) \quad (7)$$

The longstanding cell state D_{u-1} is upgraded into an innovative cell gate D_u using Eq. (8).

$$D_u = g_u \bullet D_{u-1} + j_u \bullet \hat{D}_u \quad (8)$$

The cell state can be used to decide the final result value. The output value is obtained by the sigmoid layer, as denoted in Eq. (9). Finally, $\tan h$ it is multiplied by the result of the sigmoid gate to find the cell state value, as expressed in Eq. (10).

$$p_u = \mathrm{K}\left(X_p \bullet \left[y_{u-1}, y_u\right] + c_o\right)$$

$$i_u = p_u \bullet \tan h\left(D_u\right)(10) \qquad (9)$$

Here, the output gate is represented as p_u , and the cell state is represented as D_u .

An observable pattern and the presumption that it will recur in the future serve as a basis for estimating anomalies. The expected values could significantly differ from the observed ones if this presumption is invalid. This suggests that the outcomes might include anomalous data. The divergence between the observed and predicted values is determined by analysing every point in the data. The anomalous behaviour of the data is attributed to the difference between the predicted and observed values. The average deviation in the anomalous score identifies the possibility of the anomaly. The anomaly in the data is confirmed if the uninterrupted outliers are present in the data. The anomalous score can be identified using Eq. (11). The obtained anomalous score is then transferred to the range of$[0,1]$ 0 to 1 due to the application of the min-max normalisation process.

$$p_u = \frac{\left|p_u - o_u\right|}{Average\left(\left|p_u - o_u\right|\right)} \qquad (11)$$

$$\tilde{p}_u = \frac{p_u - \min(T)}{\max(T) - \min(T)} \qquad (12)$$

The threshold value $\rho 1$ is fixed after identifying the abnormal point in the data. If the anomaly score is greater than the $\rho 1$, then the same threshold is used to mark the anomaly in the data. The abnormality of the data is also identified by fixing the threshold $\rho 2$ and the wind size X . If the threshold value $\rho 2$ is less than the number of points in the window size of the given data, it is proven that an anomaly is present in the energy metering data. This action confirms that the suspected user has stolen a certain amount of electricity. The diagrammatic illustration of the cascaded LSTM is given in Figure 3.

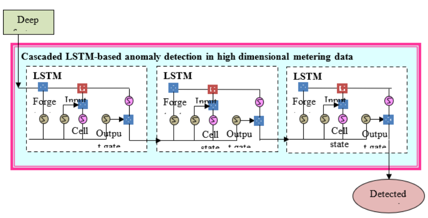


Figure 3: Cascaded LSTM for anomaly detection

Results

The performance of the dedicated system for anomaly detection, based on feature extraction in high-dimensional metering data, is analysed in the experimental process. Here, the developed cascaded LSTM model is experimented with numerous existing techniques, such as GCN-BiLSTM [28], LSTM [18], LSTM-AE [32], and BiLSTM-AE [30], using several parameters. Similarly, the proposed CAE-based feature extraction approach is compared with existing techniques, such as Principal Component Analysis (PCA) [33], Linear Discriminant Analysis (LDA) [34], Restricted Boltzmann Machine (RBM) [35], and Autoencoder (AE) [19]. The performance of the developed model, in terms of Threat Score (TS), Negative Predictive Value (NPV), kappa, Area under the Curve (AUC), accuracy, and Positive Likelihood Ratio (PLR), is briefly emphasised in this section.

$$TS = \frac{L}{L + K + J} \qquad (13)$$

$$NPV = \frac{L}{P + J} \qquad (14)$$

$$kappa = \frac{2(L * P - K * J)}{(L + K)(K + P) + (L + J)(J + P)} \qquad (15)$$

$$accuracy = \frac{L + P}{L + P + K + J} \qquad (16)$$

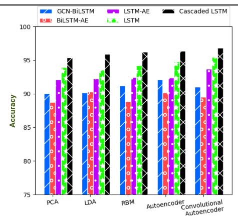
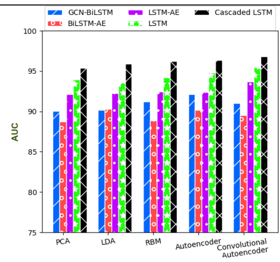
$$PLHR = \frac{LR}{KR} \qquad (17)$$

Here, the true positive and true negative are represented as L , and P respectively, the false positive and false negative are represented as K , and J correspondingly, the true positive rate and the false positive rate are expressed as LR , and KR respectively.

The proposed deep learning model, which uses a CAE and a CLSTM network, effectively detects anomalies in high-dimensional energy metering data. Its high accuracy rate of 96.36% is impressive, but it faces issues with false negatives and false positives. False positives occur when normal energy usage is incorrectly identified as anomalous, resulting in unnecessary investigations and operational inefficiencies. False negatives occur when the model fails to identify actual anomalies, such as system faults or energy theft, resulting in significant losses. The study suggests improvements like dynamic threshold settings, ensemble learning strategies, human feedback, and contextual information.

Comparison of the Suggested Feature Extraction Techniques

The performance of the developed anomaly detection model, utilising various feature extraction techniques, is illustrated in Figure 4. In this graphical illustration, the black colour chart represents the suggested model for the anomaly detection process. As mentioned in Figure 4(a), when utilising the CAE for the feature extraction process, the accuracy of the cascaded LSTM surpassed that of the existing GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM. The accuracy of the cascaded LSTM structure is minimised when the PCA approach is used for feature extraction. Figure 4 (d) shows the NPV comparison of the suggested model. Here, the CAE-based feature extraction process yields a lower NPV value since it achieves a lower reconstruction error during the feature extraction process. However, the PCA-based feature extraction process achieves a higher NPV value for the cascaded LSTM in the anomaly detection process. In Figure 4(b), the developed model achieves a higher AUC value during the anomaly detection process when employing the CAE-based feature extraction. The AUC value of the cascaded LSTM is slightly decreased when performing the feature extraction using the AE. However, the cascaded LSTM value achieves lower kappa, PLHR, and NPV values when the PCA-based feature extraction process is taken into account. Thus, the graphical illustration proved that the feature extraction capability of the CAE is better than that of the existing model, as the CAE requires a significantly smaller number of parameters for the feature extraction process compared to PCA. Additionally, the compression ratio of the CAE is enhanced than the PCA and LDA, so it is used for the feature extraction process.

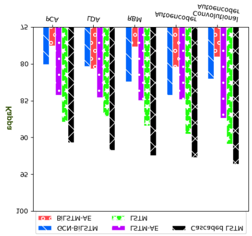
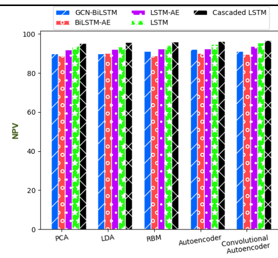
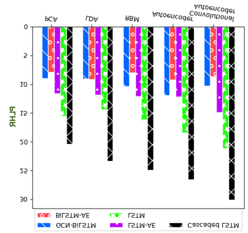
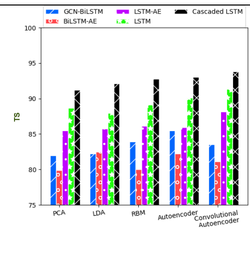
(a)	(b)
	
(c)	(d)
	
(e)	(f)

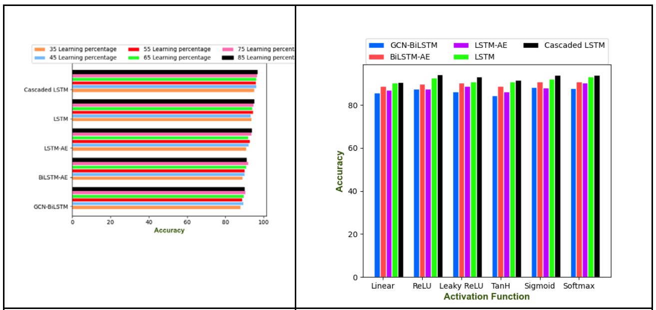
Figure 4: Performance comparison of the recommended feature extraction model in terms of (a) Accuracy, (b) AUC, (c) Kappa, (d) NPV, (e) PLHR, (f) TS

Comparison of the suggested anomaly recognition techniques

The anomaly detection performance of the cascaded LSTM is identified by varying the learning percentage. This analysis process is carried out using the Accuracy, AUC, Kappa, NPV, PLHR, and TS metrics.

Accuracy analysis of the anomaly detection process: The accuracy of the anomaly detection process, among various techniques, is identified by varying the learning percentage, as shown in Figure 5. At the 85^{th} learning percentage, the recommended cascaded LSTM model achieves a higher accuracy value compared to previously developed techniques. However, the developed cascaded LSTM model attains a lower accuracy value in the 35^{th}

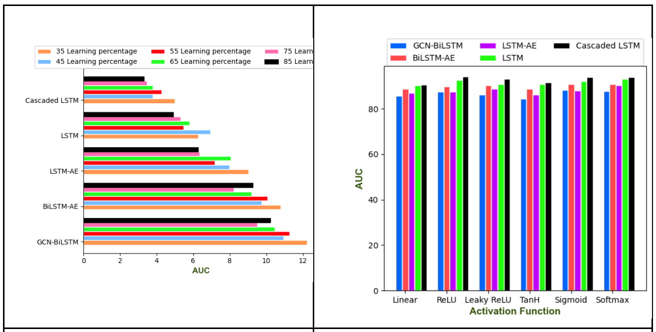
learning percentage. In all learning percentages, the GCN-BiLSTM model achieves a lower accuracy value. Similarly, the accuracy of the suggested cascaded LSTM is comparable to that of the sigmoid and tanh activation functions, and this value is higher than those of previous techniques, such as LSTM and LSTM-AE, respectively. This proved that the developed cascaded LSTM model outperforms the existing techniques by achieving the highest accuracy value.



(a) (b)

Figure 5: Accuracy examination of the recommended anomaly detection process by varying (a)Learning percentage, (b) Activation function

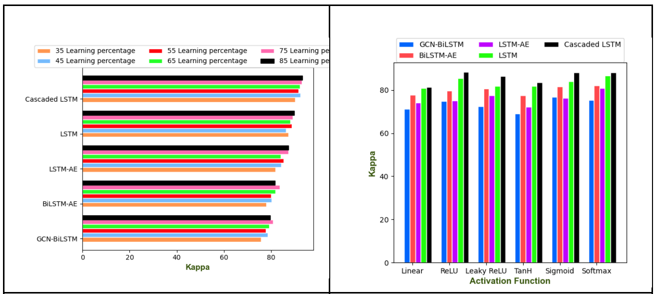
AUC analysis of the anomaly detection process: Figure 6 provides the AUC curve assessment of the developed cascaded LSTM model. The AUC of the cascaded LSTM model is analysed to determine the model's effect on the anomaly detection process. At a 75th learning percentage, the cascaded LSTM model achieves a higher accuracy value; however, this value is slightly lower when the learning percentage is set to 85. Likewise, the AUC value is slightly minimised for the cascaded LSTM at the 35th learning percentage point. The AUC metric for the suggested cascaded LSTM model is compared with various techniques, as illustrated in Figure 6(b). Here, the cascaded LSTM has a higher AUC value, which is greater than that of GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM. , Therefore, it provides higher anomaly detection compared to other techniques. This confirmed that cascaded LSTM gives the best results in the anomaly detection process.



(a) (b)

Figure 6: AUCexamination of the recommended anomaly detection by varying (a) Learning percentage, (b) Activation function

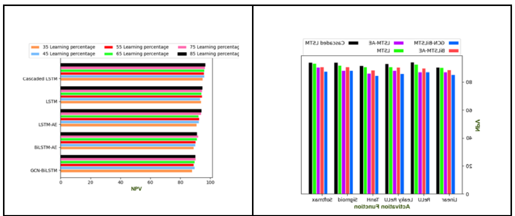
Kappa analysis of the anomaly detection process: The kappa coefficient of the developed cascaded LSTM for the anomaly detection process is illustrated in Figure 7. The developed cascaded LSTM model achieves a higher kappa coefficient at the 85th learning percentage, and the value of the kappa coefficient decreases considerably in the remaining learning percentages. According to Figure 7 (b), the kappa value of the cascaded LSTM is higher than the GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM. Suddenly, the kappa value of the cascaded LSTM increases with the ReLU activation function, but in the leaky ReLU activation function, the kappa of the cascaded LSTM is slightly lowered. This same scenario occurs with the tanh activation function. However, the suggested model makes a higher value of kappa in the sigmoid and softmax activation functions. The simulated results showed that the cascaded LSTM structure offers higher performance than the GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM for all learning percentages.



(a) (b)

Figure 7: Kappa examination of the recommended anomaly detection process varying (a) Learning percentage, (b) Activation function

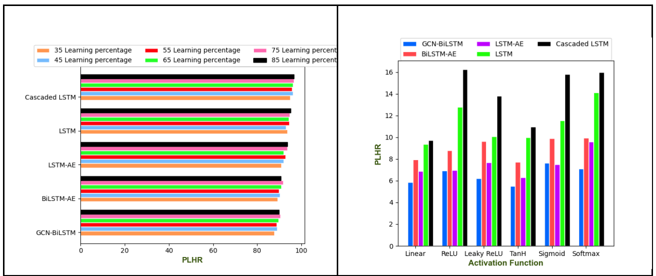
NPV analysis of the anomaly detection process: The NPV of the proposed cascaded LSTM model is compared with that of existing techniques and is presented in Figure 8. Compared to other techniques, such as GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM, the proposed cascaded LSTM achieved a better NPV value in all learning percentages. In Figure 8(b), the activation functions, including linear, ReLU, leaky ReLU, tanh, sigmoid, and softmax activation functions, are used to evaluate the performance of the cascaded LSTM in the anomaly detection process. This activation function identifies the coordination between the input and the output data. Here, the NPV value is high for the cascaded LSTM in the ReLU activation function. Yet, this value is slightly decreased in the leaky ReLU activation function and further lowered in the tanh activation function. Anyways, the cascaded LSTM model attains its initial state in the sigmoid as well as the softmax activation function. Therefore, the developed cascaded LSTM model offers a significant advantage in the anomaly detection process.



(a) (b)

Figure 8: NPV examination of the recommended anomaly detection process by varying (a) Learning percentage, (b) Activation function

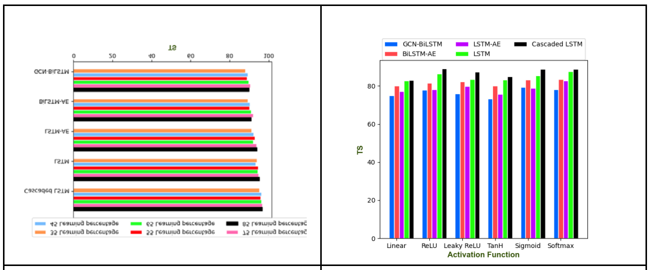
PLHR analysis of the anomaly detection process: Figure 9 offers the PLHR analysis of the cascaded LSTM model. The PLHR of the proposed cascaded LSTM model is compared with that of GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM to assess its reliability in the anomaly detection process. It is demonstrated that the cascaded LSTM model effectively identifies anomalies in high-dimensional metering data, as its PLHR value is significantly higher than that of the existing GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM models, considering a learning percentage of 85%. Likewise, the prediction performance of the cascaded LSTM is not affected because its PLHR value remains high at the 35th, 45th, 55th, and 65th learning percentages. The cascaded LSTM model is a powerful technique for detecting anomalies in high-dimensional metering data, as it achieves a higher PLHR value, as visualised in Figure 9(b). Here, the experimentation evaluation is conducted using the activation function in terms of PLHR. The performance of the cascaded LSTM is hindered in the linear activation action. On the contrary, the cascaded LSTM achieves peak PLHR value in the ReLU activation function. It has been confirmed that the cascaded LSTM outperforms previously developed techniques in identifying anomalies in high-dimensional metering data.



(a) (b)

Figure 9: PLHR examination of the recommended anomaly detection process by varying (a) Learning percentage, (b) Activation function

Time Series (TS) analysis of the anomaly detection process: The performance of the cascaded LSTM model is evaluated using the TS metric shown in Figure 10. Here, the suggested cascaded model also achieves satisfactory performance with a high TS value at the 85th learning percentage. However, the cascaded LSTM has a lower TS value in the 35th learning percentage. However, the TS value of the LSTM is slightly higher than the cascaded LSTM in the same learning percentage. When the learning percentage is set to 75, the TS value of the cascaded LSTM decreases slightly, but this value is higher than those of GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM. As mentioned in Figure 10(b), our cascaded LSTM model achieves an enhanced TS value using the ReLU activation function, and this value is consistently maintained in the sigmoid and softmax activation functions. It can be justified that the developed cascaded LSTM is effectively suited for the anomaly detection process.



(a) (b)

Figure 10: TS examination of the recommended anomaly detection process by varying (a) Learning percentage, (b) Activation function

Receiver Operating Characteristic (ROC) analysis of the anomaly detection process: The ROC curve analysis of the cascaded LSTM model is illustrated in Figure 11. The ROC identifies the information about the entire anomaly detection performance of the model. As shown in Figure 11, the ROC curve of the cascaded LSTM model is larger than the GCN-BiLSTM, LSTM-AE, BiLSTM-AE, and LSTM. The detection accuracy of the model is decided based on the ROC curve. Here, the cascaded LSTM has a large ROC, indicating that its anomaly detection accuracy is better than that of existing techniques. Hence, the anomaly detection performance of the cascaded LSTM outperforms that of existing techniques.

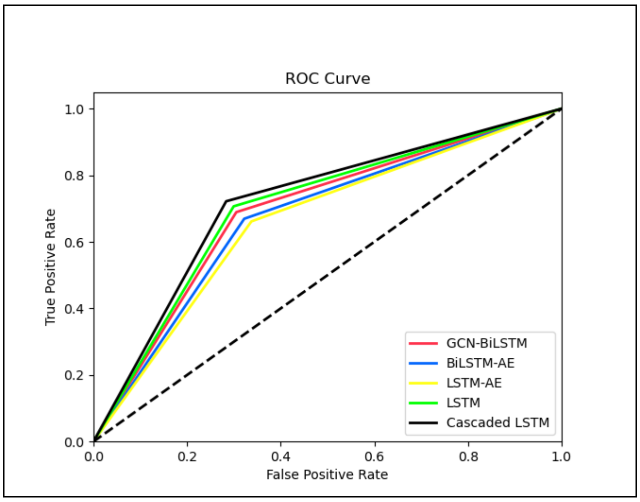


Figure 11: ROC examination of the recommended anomaly detection process

Numerical Analysis of the Anomaly Detection Process: The numerical analysis of the developed cascaded LSTM model for the anomaly detection process is presented in Table 1. Here, the accuracy of the cascaded LSTM is 96.36%, which is significantly better than that of existing techniques. In terms of all performance metrics, the developed cascaded LSTM model attains better values. Therefore, it is demonstrated that the developed model accurately predicts anomalies in high-dimensional metering data.

Table 1: Numerical assessment of anomaly detection process among various techniques

TERMS	GCN-BiLSTM [28]	BiLSTM-AE [30]	LSTM-AE [32]	LSTM [18]	Cascaded LSTM
Learning rate					
Accuracy	90.52	92.24	91.88	94.24	96.36
NPV	9.508461	7.945425	8.205953	5.868167	3.7751
Markedness (MK)	80.96673	84.77529	83.83295	88.63055	92.95135
PLHR	9.45799	12.04483	11.29997	16.47787	27.17268
Prevalence	52.81276	52.39484	52.46038	51.83354	51.28414
TS	82.78867	85.66149	85.06255	89.16479	93.01075
AUC	90.5198	92.23941	91.87952	94.23948	96.35946
Kappa	81.03913	84.47968	83.75942	88.47965	92.71981
Activation function					
Accuracy	88.36	90.76	88.16	92.08	94.04
NPV	88.4058	90.82126	88.24477	92.02899	94.04187

PLHR	7.61715	9.881474	7.492519	11.55817	15.78316
TS	79.24394	83.16327	78.91738	85.40899	88.81381
AUC	88.35933	90.75937	88.15937	92.07968	94.03959
Kappa	76.7194	81.51953	76.31952	84.15935	88.07957
Epoch					
Accuracy	90.4	91.2	93.8	94.24	95.76
NPV	90.41868	91.14332	93.88084	94.2029	95.73269
PLHR	9.4331	10.30363	15.31585	16.26272	22.44668
TS	82.57081	83.91813	88.38081	89.17293	91.91457
AUC	90.39939	91.19964	93.79942	94.23976	95.75983
Kappa	80.79941	82.39928	87.59968	88.47953	91.51965

Conclusion

A deep learning-based cascaded framework was developed in this work to detect anomalies in high-dimensional energy metering data. Initially, the high-dimensional energy metering data underwent a deep feature extraction process using the CAE structure. This process helped eliminate redundant information from the high-dimensional energy metering data. After the feature extraction process, a cascaded LSTM was suggested to detect anomalies in high-dimensional energy metering data. The cascaded LSTM was formed by cascading the three basic LSTM structures; here, the output from the previous structure was passed to the next structure to get the outcome. In the cascaded LSTM, the first LSTM structure analysed the huge dataset and yielded less accurate results. The second LSTM takes a significantly smaller amount of data compared to the first structure, as it has already processed the data flagged by the first LSTM. The final LSTM structure in the cascaded network identified the anomaly in the data by fixing the threshold value. The proposed deep learning-based anomaly detection model enhances energy management systems by accurately identifying abnormal energy usage in complex, high-dimensional data. Using a CAE and Cascaded LSTM network enables early fault detection, reduces energy waste, supports real-time monitoring, and improves decision-making. Its scalability and adaptability make it ideal for diverse energy environments, contributing to more efficient and cost-effective energy management. Finally, the suggested model was compared with previously developed technique to confirm its efficacy in the anomaly detection process. The results showed that the anomaly detection efficacy of the developed cascaded LSTM on high-dimensional metering data was superior to that of previously developed techniques.

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