Engineering Applications of Artificial Intelligence 119 (2023) 105775

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

An innovative deep anomaly detection of building energy consumption using energy time-series images

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ARTICLE INFO

Keywords:
Deep anomaly detection
Building energy consumption
Hyper-parameter variation
Neural network activation
Transfer learning

ABSTRACT

Deep anomaly detection (DAD) is essential in optimizing building energy management. Nonetheless, most existing works concerning this field consider unsupervised learning and involve the analysis of sensor readings through a one-dimensional (1D) energy time series, which limits the options for detecting anomalies within the building's energy consumption. To the best of the authors' knowledge, this paper presents the first study that explores using two-dimensional (2D) image representations as features of a supervised deep transfer learning (DTL) approach. Specifically, using 2D image representations allows taking advantage of any underlying data within the feature set, providing more possibilities to encode data and detect pertinent features which may not be considered in standard 1D time-series. Furthermore, the effects of using CNN activations as machine learning (ML) model features are also investigated to combine the advantages of both techniques. Additionally, the concept of layer and hyperparameter variation for the CNN model is also studied, with the objective of reducing the overall time computation and resource requirements of the proposed system. Hence, this makes our approach a candidate for edge-based applications. As per the conducted experiments, the top methodology rests at the F1-scores of 93.63% and 99.89% under simulated and real-world energy datasets, respectively. This involves using grayscale 2D image representations that combine CNN activations extracted from AlexNet and GoogleNet pre-trained models as features to a linear support vector machine (SVM) classifier. Finally, the comparison analysis with the state-of-the-art has shown the superiority of the proposed method in various assessment criteria.

1. Introduction

1.1. Preliminary

Projections considering current energy policies demonstrate that global electricity consumption will grow by 84% in the next 25 years (Alsalemi et al., 2022; Himeur et al., 2022d). As such, energy efficiency is a core element for most countries worldwide. For instance, the European Union (EU) has set significant challenges for energy and climate policy, such as the 40/27/27 objectives (40% increase in energy efficiency, 27% reduction of CO2 emissions, and 27% integration of renewable energies by 2030) and also a significant prerequisite to moving forward towards to 80%–95% reduction in greenhouse gas emissions by 2050 (Himeur et al., 2020a; Sayed et al., 2021). Information and communication technologies (ICT) are an essential means by which energy efficiencies may be achieved (Deng et al., 2020). However, consumers and even managers are still hesitant to widely adopt ICT technologies that contribute to energy efficiency for many and diverse reasons (Sayed et al., 2022b), such as (i) the lack of demonstration of their cost-effectiveness (Al-Kababji et al., 2022), (ii) the current under-development of applications that exploit energy usage data for the benefit of consumers and designated third parties (Varlamis et al., 2022b), (iii) the lack of demonstration that energy savings can be achieved without compromising comfort levels (Himeur et al., 2022b) and (iv) limitations on consumers' capacity or capability to make the necessary changes in energy usage habits (Deng et al., 2022b,a). Furthermore, the vast majority of buildings' customers are not exposed to price signals provided in multiple ways via different pricing models and rate designs (Sardianos et al., 2021). Typically, driven by

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https://doi.org/10.1016/j.engappai.2022.105775
Received 24 September 2022; Received in revised form 22 November 2022; Accepted 22 December 2022
Available online 6 January 2023

technological and industrial development, the growing population, and the need to improve living standards, the upwards trend of energy consumption in buildings cannot be curbed easily. Indeed, the building energy sector is responsible for almost 40% of energy consumption and up to 45% of CO_2 emissions around the globe (Benavente-Peces and Ibadah, 2020; Varlamis et al., 2022a). While different approaches have been recently investigated, such as renewable energy and the conception of green buildings (Fu et al., 2022; Song et al., 2023), they remain very costly and not accessible to the population. To that end, there has been a move to adopt novel technologies based on ICT, artificial intelligence (AI) and machine learning (ML), Internet of things (IoT), edge and cloud computing, etc., for promoting building energy-saving (Manimala, 2021). Therefore, using these technologies along with advanced metering infrastructure, smart distribution boards, and renewable energy has given rise to "smart grid (SG)" (Himeur et al., 2022e; Elnour et al., 2022).

The increasing energy consumption of buildings is also because most buildings are not performing as expected by their designers/managers (Ma et al., 2021; Deng et al., 2021) . Specifically, buildings are consuming 20% more energy than necessary due to end-users incorrect energy consumption habits and lack of awareness, malfunctioning equipment, faulty devices, improper operating processes, and wrongly configured monitoring systems (DOE, 2015). In this line, the building systems may fail to meet the performance expectations due to various faults. Poorly maintained, degraded, and improperly controlled equipment wastes an estimated 15% to 30% of energy used in commercial buildings (Himeur et al., 2020b). Therefore, it is of great potential to develop automatic, quick-responding, accurate, and reliable fault detection and to provide diagnosis schemes to ensure the optimal systems operations to save energy (Alsalemi et al., 2021). Developing efficient building energy-saving systems aims at (i) early detection of abnormal energy consumption and (ii) prevention of energy frauds from smart meters. Put simply; this enables operators/end-users to foresee uncommon events, identify unusual energy consumption behaviors, and detect abnormal energy usage. In this regard, developing anomaly detection of energy consumption (ADEC) is becoming a widely recognized research topic, which attracts significant interest from both artificial intelligence and energy research communities (Himeur et al., 2021c). An energy consumption anomaly can be either a pattern or a contextual anomaly. A pattern anomaly usually represents an outlier whose value differs considerably from the neighboring energy consumption values. It can be due to the malfunction of some devices (or systems), noise impulses generated by some devices on the grid when turned on, or temporary interference of sensor readings (Himeur et al., 2021a). On the other hand, a contextual anomaly represents a set of energy consumption patterns that are abnormal in a specific period of time. However, on the individual level, their values may fall within the normal energy consumption range. Different reasons can cause this kind of anomaly, including (i) excessive energy consumption due to end-users' behavior, (ii) excessive consumption of faulty devices or systems, and/or (iii) excessive consumption of energy-greedy devices (Liu et al., 2020; Himeur et al., 2021b).

Anomaly detection is the process of identifying events or observations that do not conform to expected behavior or pattern. Typically, these anomalous observations can be translated into important information about the health status of the system under study (Himeur et al., 2022c). For example, they can be faults, malfunctioning in the systems, or suspicious or unwanted behavior that requires immediate attention and/or measures. With the advent of IoT-based and smart technologies enabling the acquisition and access to an abundant amount of data, data-driven approaches have become more attractive for anomaly detection. They have been widely deployed for several application domains such as in Elnour et al. (2020a), Yun et al. (2021), Han et al. (2019) and Bang et al. (2019) for fault detection in heating, ventilation, and air conditioning (HVAC) systems, in Noorizadeh et al. (2021), Elnour et al. (2020b), Karimipour et al. (2019) and Elnour et al. (2021) for attacks and intrusion detection in industrial control systems, in Rtayli and Enneya (2020) and Paruchuri (2017) for fraud detection, and in Chiosa et al. (2021), Rashid and Singh (2018) and Sial et al. (2019) for detecting ADEC in buildings. Using ML for anomaly detection makes developing detectors relatively easier and faster (Sayed et al., 2022c). Unlike basic anomaly detection approaches that require expert knowledge and potentially hand-crafted representations or rules, the development of ML-based anomaly detection systems requires a fair amount of good-quality data that are generally available in abundance and a comprehensive process of parameter tuning of the ML algorithms used (Himeur et al., 2022a). The last step can be time-consuming but can be fully automated and optimized with the advancement in the computation systems. Moreover, the application of ML for anomaly detection helps enhance and improve the process's performance, as well-chosen/developed ML models can achieve high accuracy and reliability compared to the primary detection methods (Sayed et al., 2022a).

1.2. Open challenges

On the other hand, deep learning (DL) has recently shown tremendous success in tackling complexities related to high dimensionality, data inter-dependency, and data heterogeneity in a wide range of applications (Pang et al., 2021). On the other hand, in their original forms, DL techniques were found inapplicable for anomaly detection applications due to the characteristics of anomalies such as rarity, heterogeneity, boundless nature, and prohibitively high cost of collecting large-scale anomaly data (Pang et al., 2021). Even with that, the research community successfully developed frameworks to adapt and deploy DL algorithms to fit the anomaly detection problem, such as by using unsupervised learning (Fan et al., 2018), feature extraction methods (Himeur et al., 2020b), etc. This helped overcome the major challenges to which shallow anomaly detection methods fail in different application contexts.

Besides, a fundamental challenge stems from the fact that the unsupervised learning approaches do not deploy any prior knowledge of the anomalies, hence the weak performance of those approaches in detecting complex and sophisticated anomalies. Those anomalies, which can be very serious, can go undetected for a long while. Studies, such as Tasfi et al. (2017), suggested harnessing the available historical data such that the limited available labeled data, along with the unlabeled data, are exploited to develop a form of semi-supervised deep anomaly detection (DAD) frameworks. Such approaches do not completely eliminate the challenge, but they are regarded as fruitful attempts to handle the problem. Other challenges rarely addressed are the robustness and resilience of DAD approaches to noise presence and adversarial observations. For that, hybrid methods combine DL algorithms with expert knowledge to make a convenient mitigation measure that boosts the detection's reliability and performance, despite the complexity of the development stage.

Moving on, when detecting anomalies with traditional ML algorithms, there exists a major issue related to the high false-positive rate. This is because most conventional ML models classify any unseen observation as an anomaly. However, it may be a normal sample that has not been included in the training ensemble. One theoretical idea to overcome this issue is to have a large-scale training data set consisting of all possible normal cases. However, in practice, this cannot be guaranteed. Typically, even if it is possible to augment the training data set to include much more normal observations, a model with a high generalization ability will still be needed. To that end, using DL models instead of conventional ML algorithms may have a better ability to generalize.

1.3. Motivation of the study

In this context, convolutional neural networks (CNN) models have become a prevalent ML technique, which provides promising performance when treating data with images as inputs. This is because of their ability to read, process, and extract the most pertinent characteristics of 2D data (Wang et al., 2021). Thankfully, although data is not formatted as an image in some applications, different transformations can be explored to help apply CNN models to other data formats. Energy time series is among these kinds of data which can be transformed to address a problem from a computer vision context. Consequently, transforming energy time series into 2D representations creates more possibilities for analyzing, encoding, and interpreting energy samples. Furthermore, different square kernels can be applied to analyze the correlation between them (Himeur et al., 2021a). For example, in various classification problems, such as the electrocardiogram (ECG), electroencephalogram (EEG), and non-intrusive load monitoring (NILM), two-dimensional (2D) images are produced from the one-dimensional signals, which allows applying popular image processing and CNN algorithms. For instance, in Jun et al. (2018), an ECG classification scheme using a 2D-CNN is proposed, where each ECG beat is first represented in 2D space and then fed into a CNN classifier. Moving on, Xavier initialization, data augmentation, batch normalization, and dropout have been utilized to optimize the performance of this architecture. Furthermore, in Li et al. (2020), a two-stream CNN based on the current time–frequency feature fusion for NILM is introduced. A time-series image transformation approach to fuse current time–frequency multi-feature is first developed for this case. Subsequently, a two-stream DL aggregating 2D-CNN and gated recurrent unit (GRU) is presented.

1.4. Contribution

Based on the aforementioned discussion and the identified issues, it is of utmost importance to develop powerful DAD algorithms for ADEC, which can (i) avoid overfitting, (ii) reduce the number of false positive alarms, and (iii) enable better interpretation of the feature used to classify data and obtained outcomes. In this context, developing a DAD solution based on using energy time-series images can help achieve these goals. To that end, this work aims to determine the optimum method for ADEC in sustainable buildings, considering the overall accuracy and time and resource requirements as the basis of the experimental comparisons. A detailed study is conducted on the advanced applications of 2-D image representations and pre-trained neural networks for ADEC. As per the literature review, studies concerning these methodologies are limited, particularly for the selected application of this research. With the current rising trend of artificial intelligence, exploring this research area provides a suitable baseline for future advancements within this topic. Furthermore, findings within this work can also be extended to other domains. Overall, the main contributions of this study can be summarized as follows:

- Conduction of a thorough literature review on ADEC to identify the pros and cons of existing methods, including conventional ADEC and DAD.
- Direct application of transfer learning via pre-trained NN models using 2D representations of time-series energy signals.
- Hyper-parameter and layer variation on pre-trained CNN models.
- Direct uses pre-trained models as a feature extraction technique by extracting neural network activations on a specific layer and using them as features to differing ML approaches.
- Utilization of hyper-parameter varied pre-trained models as feature extraction methods in conjunction with ML approaches.

The remainder of the paper is organized as follows. Section 2 discusses the related works for ADEC in buildings using ML algorithms and the main drawbacks and limitations. Section 3 details the proposed approach's details, where the datasets, processing stage, CNN models, and transfer learning algorithms proposed in this study are deeply explained. The empirical evaluation results are then presented under different experimental and simulation scenarios in Section 4. Lastly, concluding remarks and outlook are derived in Section 5.

2. Related works

ADEC can be performed using supervised or unsupervised learning. Supervised learning requires anomaly benchmarks, which represent the abnormal energy consumption values against which detected anomalies can be compared to avoid false alarms. In this section, we briefly reviewed conventional ADEC and DAD techniques.

2.1. Conventional ADEC methods

Conventional ADEC techniques have been widely used in the building energy sector due to their implementation simplicity and low computational cost. For instance, in Araya et al. (2017), a pattern-based anomaly detection scheme is proposed, named collective contextual anomaly detection based on sliding windows (CCAD-SW). Typically, abnormal energy profiles are detected using overlapping sliding windows. Moreover, an ensemble classifier is developed by combining various classifiers using a majority vote; this results in ensemble anomaly detection (EAD). The latter has been evaluated using real-world energy consumption footprints from different buildings (in Brampton, Ontario, Canada). Moving forward, a data-driven ADEC scheme using a spatiotemporal feature extraction technique is proposed in Liu et al. (2017), which relies on the paradigm of symbolic dynamics to discover and represent causal interactions among subsystems. Then, the extracted features are fed into a restricted Boltzmann machine (RBM), which has been utilized to learn system-wide patterns and form an energy abnormality detection system.

In Yip et al. (2018), linear programming (LP)-based ADEC technique is introduced to evaluate consumers' energy consumption habits, identify faulty meters, and prevent the potentiality of energy frauds. Typically, this method allows (i) capturing energy theft attacks against advanced metering infrastructure (AMI), (ii) pinpointing sub-meter defects in SG environments, and (iii) overcoming some issues related to the non-technical loss (NTL) detection. In Capozzoli et al. (2018), Capozzoli et al. put forward an ADEC scheme by analyzing energy time series in buildings and identifying unexpected and unusual power consumption habits. This methodology is built by (i) using an improved symbolic aggregate approximation procedure and (ii) optimizing the tuning of the time-window length and symbol intervals with reference to power consumption activities.

By contrast, an unsupervised ADEC approach for integrated energy systems (IESs) is proposed in Zhang et al. (2021) by combining four ML models, namely clustering analysis (CA), knowledge-based (KB), one-class support vector machine (OCSVM) and isolation forest (IF). Specifically, this framework enables detecting and analyzing possible vulnerabilities and threats of an IES with regard to the modifications and changes of the operation status and run-time of every subsystem in the IES. Similarly, Do et al. (2018) propose an unsupervised and scalable ADEC scheme using a mixed-variate RBM (Mv-RBM), which refers to a principled-probabilistic technique for estimating the density of mixed data. The free energy extracted from the Mv-RBM has been used as the abnormality score because it is similar to data negative log-density up to an additive constant. Following, this process has been extended for detecting abnormalities through multiple levels of data abstraction, where the MIXed data Multilevel Anomaly Detection (MIXMAD) solution is developed by constructing an ensemble of mixed DBNs having changing depths. Following the same concept, an unsupervised ADEC is introduced in Rashid and Singh (2018) to identify anomalous daily energy consumption in buildings based on identifying patterns in the smart meters data. The local outlier factor (LOF) is used for clustering the data into clusters of the various energy consumption patterns. For each resultant cluster, a local abnormality score is computed using all data points within the particular cluster to reduce the false alarm rate. An anomalous consumption is identified if it is significantly different from the prominently identified pattern of the cluster.

In Sial et al. (2019), four different ADEC schemes in hostel buildings are investigated using (i) percentage change in consumption (PCC), (ii) k-nearest neighbor (kNN), (iii) histogram buckets (HB), and (iv) principal component analysis (PCA). Smart meter data is grouped based on the hour of the day, type of the day, and type of power supply and then pre-processed to normalize the data and fill in missing ones to enhance the data analysis. In the 4 schemes, an anomaly score is computed and then used to identify abnormal consumption based on a defined threshold using a percentage confidence interval. Moving on, an ADEC framework at the building level is proposed in Chiosa et al. (2021), followed by the diagnosis at the appliance level to identify the source of detecting anomalous consumption. Frequent and infrequent aggregated energy patterns are identified using regression trees (RTs) and an adaptive symbolic aggregate approximation (aSAX) process. Then, association rule mining (ARM) is used to uncover the sub-load(s) responsible for the detected anomaly. While in Xu et al. (2021), anomaly detection and dynamic energy performance evaluation of HVAC systems are presented using ARM and clustering analysis to identify the energy patterns and the relevant association rules to detect and diagnose abnormal energy consumption.

In Zhou et al. (2021), ADEC is performed to detect anomalous energy patterns of central air conditioning systems (CACS) by formulating the problem as binary classification. Data pre-processing is performed then information entropy (IE) is used to characterize the daily consumption patterns to mitigate the issues of high miss rates and high false-positive rates. The data pre-prepossessing partially requires expert experience. Then, a dataset of the normal daily energy consumption patterns (NDECP) is created and continuously updated online, and then non-conforming data patterns to the NDECP are flagged anomalous. Additionally, a model-based fault detection method is proposed in Bang et al. (2019) using the building simulation model to detect abnormal energy consumption of ventilation systems in buildings. A baseline is created based on the building simulation model that is compared with the actual data of building operation based on the Chernoff bound method that defines the allowable deviation from the baseline before identifying the instance anomalous.

2.2. Deep Anomaly Detection (DAD)

Using DL for anomaly detection, also called DAD, has emerged as a promising direction. Typically, DAD aims at detecting outliers (also called out-of-distribution patterns) by assigning anomaly scores to data inputs (Zhang et al., 2022). DAD has excelled in identifying abnormalities in complex and large-scale datasets, e.g., time series (Zhou et al., 2022), speech (Garoufis et al., 2022), ECG (Srivastava et al., 2022), images (Yousefan et al., 2022), and videos (Wu et al., 2022). To that end, increasing attention is devoted by the building energy sector to developing DL-based ADEC frameworks. For example, in Fan et al. (2018), a deep autoencoder (DAE) based energy consumption anomaly detection scheme is proposed. In doing so, a DAE-based ensemble approach is constructed by combining different architectures. Also, the potential of various DAE models is examined, such as convolutional autoencoders (CAE), denoising autoencoders, recurrent autoencoders (RAE), etc. In Hollingsworth et al. (2018), the authors investigate energy prediction and ML models for detecting energy consumption anomalies. Therefore, an energy forecasting scheme based on autoregressive integrated moving averages (ARIMA) combines long short-term memory (LSTM) to analyze day-to-day operations and remove seasonality and trends from energy observations. Similarly, an energy efficiency optimization technique for reducing energy waste has been suggested in Yin et al. (2022) by exploiting abnormal energy consumption and using an innovative algorithm called "rain flow-based mean nearest neighbor distance anomaly factor." Also, in Wang et al. (2019), residual-based anomaly detection for energy consumption is proposed using an LSTM NN that is used to forecast the energy consumption, and then the difference between the actual and predicted values is used as the indication of the status of the energy consumption based on static threshold settings. In another residual-based anomaly detection mechanism, authors (Yang et al., 2022) have utilized learned models to predict and generate residuals for anomaly detection Predictions from the learned models are used to generate the residuals for anomaly detection by Page's cumulative sum test. In a similar way, an unsupervised anomaly detection approach for detecting anomalous energy usage in residential buildings is introduced in Xu and Chen (2020b), which is based on recurrent neural network with quantile regression (RNN-QR). In this regard, this approach relies on predicting energy consumption before identifying abnormal patterns.

Moving on, Pereira and Silveira (2018) propose a scalable, unsupervised, and generic system for pinpointing anomalies in energy consumption time-series data. Accordingly, a variational self-attention mechanism (VSAM) has been used to introduce attention in the model, improving the encoder and decoder operation. Next, abnormalities are detected using the probabilistic reconstruction scores provided by our model. A CNN-based consumption anomaly detection for building automation and management systems (BAMSs) is proposed in Tasfi et al. (2017). It aims to accommodate sparsely labeled datasets such that the framework consists of a supervised CNN-based auto-encoder, which has branches at the output (i.e., reconstruction branch and classification branch) to produce two outputs. These are the classification label and the reconstructed signal. The network's branches are trained independently based on the availability of data labels in the training dataset. In situations where the training sample is unlabeled, only the network parameters of the reconstruction branch are updated. The two outputs of the network are used to deduce the final decision. Li et al. (2022) have proposed an unsupervised deep generative model capable of identifying whether the current state of the nuclear power plant is in normal operation or in accident condition. The main advantage of their approach that by only making use of normal operation data from the nuclear power plant, the approach is effectively detecting the abnormal operation state.

In Fenza et al. (2019), an LSTM network is deployed to forecast the consumers' behavior based on their consumption to isolate actual anomalies from normal behavioral changes such as family structure change, a house becoming a second residence, etc. At first, clustering analysis is used to identify energy consumption profiles from the time-series data. Then the LSTM-based model is developed using the outputs of the clustering analysis to forecast future individual consumption with respect to the most common profiles, and further analysis is conducted on the forecasting error to identify potential anomalies in such behaviors.

To address the increased sophistication and complexity of cyber–physical system attacks and to handle the massive increasing volume of data, domain-specific knowledge is required, which can then be directly applied to analyze these challenges. To conduct research considering these challenges in mind, Nagarajan et al. (2022) proposed an intelligent mechanism that combines CNN with a Gaussian-Mixture Model (GMM) based on the Kalman Filter (KF). The model is capable of detecting anomalous behavior in cyber–physical systems. In Chahla et al. (2020), a framework for daily consumption anomaly detection and isolation is proposed using an NN-based auto-encoder (AE-NN) for anomalous consumption detection and a hybrid structure combining K-means clustering algorithm and an LSTM network to localize the anomaly throughout the day, which promotes the detection of abnormal behavior based on the assumption that identical daily consumption can repeatedly appear due to users' living habits. While an anomaly detection framework for ground source heat pump (GSHP) systems in buildings, being one of the great energy consumers, is proposed in In Xu and Chen (2020a) using a mode decomposition-based LSTM algorithm for consumption prediction. The difference between the predicted and actual values is used to identify the abnormal system energy consumption by Grubbs' test. In Himeur et al. (2020b), a rule-based scheme that deploys the micro-moment paradigm as a feature extraction module is used to categorize power consumption data into five distinctive classes based on consumption status, occupancy, and appliance use. Then, a deep neural network (DNN) and complementary ensemble empirical mode decomposition (CEEMD)-based anomaly classifier is developed to automatically identify the five abnormal consumption classes.

Table 1 summarizes the ADEC frameworks discussed above, the ML models used in each study, their characteristics, application scenarios, and limitations.

2.3. Critical discussion

By overviewing existing ADEC frameworks, a set of limitations and open challenges have bee identified as follows:

- The comparison study presented in Table 1 shows that most overviewed ADEC methods rely on unsupervised learning. This is mainly due to the simplicity of its implementation compared to supervised learning and the lack of annotated datasets. In this line, by applying unsupervised ADEC methods on large-scale datasets, the anomaly detection performance and computational efficiency are often dramatically degraded. Moreover, it is hard to properly assess the performance of the applied ADEC models because of the unavailability of annotations.
- By analyzing existing ADEC frameworks based on conventional ML and DL models, it was clear that a tangible definition of abnormal energy consumption is essential to developing robust ADEC models. However, this is quite challenging in different energy data sets because of (i) the nature of buildings, (ii) the variety of equipment, devices, and appliances installed in each building, (iii) the type of data collected from each building, etc. On the other hand, despite the tremendous effort that has been made to put into action ADEC techniques using conventional ML and DL techniques, different limitations and drawbacks persist and need to be overcome to (i) improve the performance of ADEC solutions for detecting abnormalities, (ii) reduce their complexity, (iii) and enable their implementation on edge platforms. Specifically, it is still challenging to reach convincing anomaly detection performance using unsupervised learning models since the rationality of ADEC results would only be carried out by posterior analysis while most existing datasets are unlabeled.
- Despite that some unsupervised data mining schemes were utilized to improve the performance of energy big data analysis, the corresponding post-mining workloads could be immense. Concretely, selecting non-redundant and relevant association rules representing abnormal and normal energy consumption usage could be laborious (Li et al., 2017; Fan et al., 2015).
- The performance of existing unsupervised ADEC techniques considerably depends on the characteristics employed. Thus, features for ADEC are constructed using simple statistics (e.g., the mean and standard deviation of numerical variables) or domain expertise. However, complex statistical models are subject to stringent mathematical assumptions and are not scalable to large-scale datasets, which can cause problems when processing real-world high-dimensional data.
- The generalizability of ML models needs to be improved, mainly because there is often a gap between the data distribution of the source domain (used for training) and the target domain (used in testing). This means that real-world data used in testing often differ from training data, although both are related.

2.4. Novelty and innovation of the proposed method

To overcome the above-mentioned limitations, some studies have suggested using auto-encoders as they can adopt the CNNs for developing unsupervised ADEC, where the models' input and output are set identically. However, auto-encoders are not that efficient compared to CNN, and generative adversarial networks for anomaly detection (Gonzalez et al., 2022). Typically, their performance can be drooped if insufficient training data is available (Takiddin et al., 2022). Furthermore, the rapid development of CNN models has provided great opportunities to analyze 2D signals and detect faulty and anomalous variables, especially if annotated data sets are used. More importantly, CNN provides data-driven approaches to extract features at different levels, which is very useful for processing the most challenging tasks of ADEC in buildings.

In contrast, in this study, we propose a supervised ADEC approach that exploits the representation of energy time-series signals in 2D space to feed different pre-trained CNN models. Typically, a DTL strategy has been developed by fine-tuning pre-trained models, such as GoogleNet and AlexNet, on two energy consumption datasets to detect abnormal energy usage. These models are efficient in reading, processing, and extracting the most relevant features of 2D data. Moreover, CNN activations have then been used as ML features to improve the performance of the proposed methodology. On the other hand, using DTL and pre-trained CNN models can considerably (i) reduce the complexity of the ADEC solution as there is no need to retrain these models from scratch and (ii) improve the generalizability of the proposed solution on other energy consumption datasets recorded from other buildings or even in other regions.

3. Proposed ADEC methodology

This section details the different methodologies explored within the context of this work, elaborating on justifying the advantages and highlighting the points of improvement of each technique. The section begins by introducing the data sets utilized for the experiments and the pre-processing methods applied to meet the specifications of the models used. It then extrapolates on the various techniques compared, progressively identifying the research gaps addressed within this work.

3.1. Dataset description

To evaluate the performance of the proposed DAD scheme, the simulated energy dataset (SiD) introduced in Himeur et al. (2020b) and the Dutch residential energy dataset (DRED) (Uttama Nambi et al., 2015) are considered. These datasets have been selected because they include labels of normal and abnormal energy consumption footprints. Specifically, SiD represents an annotated micro-moment-based energy usage dataset produced using human behavior modeling of real power consumption footprints from Bache and Lichman (2013). It comprises ten feature sets generated based on energy usage and occupancy data. By contrast, DRED is a real repository that includes energy consumption, occupancy, and environmental data of one pilot household (in the Netherlands) (Uttama Nambi et al., 2015). Sensor devices have been set to record aggregated and appliance-level power consumption. This dataset has been annotated using the same process as SiD, which generates five sets of features corresponding to energy consumption and occupancy data.

3.2. Pre-processing and conversion of time-series data to 2D images

In this work, we represent the sensor readings derived from the SiD and DRED datasets into time-series 2D images, which will then be used as the main input for the models, regardless of their usage, which, in this work, can range from regular transfer learning, hyperparameter varied model, or NN activation extraction. This is achieved by creating a matrix representation of the sensor readings, followed by normalizing the values. In the grayscale domain, normalization is achieved by dividing all matrix samples by the maximum value, which is 255. Accordingly, a similar process is done with the RGB domain. Once the values are normalized throughout the entire matrix, this is resized into the required image size, as given by the pre-trained model.

Table 1
A summary of ADEC frameworks discussed in this paper.

Work	ML model	Learning process	Description	Application	Inconvenient
Bang et al. (2019)	Model-based	Unsupervised	Detect anomalous energy consummation	Fault detection	Requires developing the building dynamic simulation model
Chiosa et al. (2021)	RTs, aSAX, ARM	Unsupervised	Detect anomalous energy consummation at the building level and diagnose the source at the sub-loads level	Anomaly detection and diagnosis	The extraction of association rules and development of classification trees can result in information loss and accuracy decrease.
Rashid and Singh (2018)	LOF	Unsupervised	Detect anomalous daily energy consummation	Anomaly detection	High FNR for hourly consumption anomalies
Sial et al. (2019)	PCC, kNN, HB, PCA	Unsupervised	Detect anomalous energy consummation	Anomaly detection	Does not address the mitigation of the potential high false-positive rate problem
Capozzoli et al. (2018)	Aggregate approXimation	Unsupervised	ADEC based on enhanced symbolic aggregate approXimation (SAX) process	Anomaly detection	High computational complexity due to using a time-windowing process.
Tasfi et al. (2017)	CNN	Semi-supervised	DNN with confidence sampling based on two sub-networks	Anomaly detection	Assumes the availability of partially labeled data
Fenza et al. (2019)	Clustering, LSTM	Unsupervised	Forecast the consumers' behavior to isolate actual anomalies from normal behavioral changes	Anomaly detection	High computational cost and moderate anomaly detection accuracy.
Araya et al. (2017)	CCAD-SW, EAD-CCAD-SW	Unsupervised	Ensemble anomaly detection by combining multiple classifiers using majority voting	Anomaly detection	Less interpretable and it is challenging to predict and explain the output. Expensive in terms of both time and space.
Liu et al. (2017)	RBM	Unsupervised	ADEC using energy-based spatiotemporal graphical modeling	Anomaly detection	Difficult to accurately assess the performance as it is based on an unsupervised learning process.
Yip et al. (2018)	LP	Unsupervised	Detecting energy theft attacks against AMI	NTL detection	Require annotated data
Zhang et al. (2021)	CA, KB, OCSVM,IF	Unsupervised	Vulnerability dynamic analysis for large-scale integrated energy systems	vulnerability dynamic analysis/anomaly detection	N/A
Do et al. (2018)	Mv-RBM	Unsupervised	Unsupervised anomaly detection by estimating the density of mixed data.	Anomaly detection	The time complexity increases linearly with the number of data types.
Xu et al. (2021)	Clustering analysis, ARM	Unsupervised	Detect anomalous HVAC systems energy consummation	Anomaly detection and diagnosis	The time complexity grows with large-scale datasets.
Zhou et al. (2021)	IE	Unsupervised	Detect anomalous CACS daily energy consummation	Anomaly detection	Require expert knowledge
Hollingsworth et al. (2018)	ARIMA, LSTM	Unsupervised	Anomaly detection using DL-based energy time-series forecasting	Anomaly forecasting	The lack of interpretability.
Wang et al. (2019)	LSTM	Unsupervised	Detect anomalous energy consummation	Anomaly detection	Uses conventional thresholds setting scheme
Chahla et al. (2020)	AE-NN, K-mean clustering, LSTM	Unsupervised	Detects daily anomalous consumption and localize anomalies throughout the day	Anomaly detection and isolation	Detect anomalies without specifying at what time they have occurred.
Xu and Chen (2020a)	LSTM + CEEMD	Unsupervised	Predict the consumption of GSHP pumps and statically analyze the consumption prediction error to detect anomalous	Anomaly detection	High computational cost due to the combination of LSTM and CEEMD.
Himeur et al. (2020b)	Micro-moments, DNN	Supervised	Label consumption data and then diagnose anomalous consumption type based on energy amount, occupancy, and/or appliance use	Anomaly diagnosis	Require data annotation.

This process is achieved using bi-cubic interpolation. The images are then concatenated in three dimensions to create an RGB format per the models' requirements and converted into a grayscale color map array.

On the other side, different transformation techniques have been proposed in the Literature to transform time-series into images. This aims to provide more insights into the characteristics and patterns which are invisible in the initial time-series' 1D sequences. As explained in Fig. 1, a list of features for a given instant is arranged into a 5 × 5 matrix. As per our previous experiments, the grayscale color map returned the highest accuracy as our previous experiments with traditional transfer learning compared to the jet color map representation. Fig. 2 displays the grayscale representation of a set of readings from the

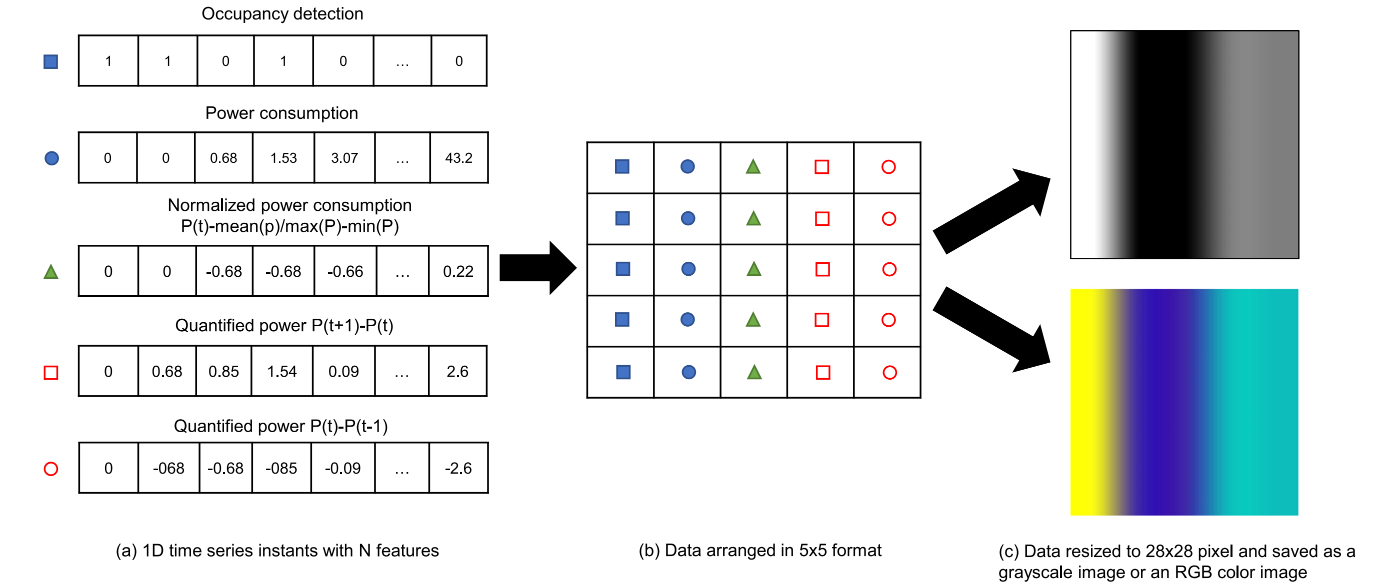

Fig. 1. Overview of the conversion of 1D time-series to 2D images.

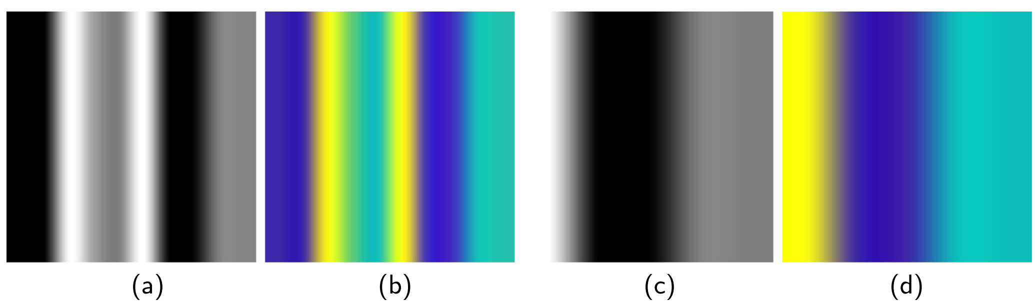

Fig. 2. (a) Grayscale Image Representation for Simulated Data, (b) Jet Colormap Image Representation for Simulated Data, (c) Grayscale Image Representation for Real Data, (d) Jet Colormap Image Representation for Real Data.

simulated dataset with 8 features. These images are also resized into the relevant image size requirement of the pre-trained model through bi-cubic interpolation coupled with anti-aliasing. Specifically, Figs. 2(a) and (b) show the grayscale and jet colormap representations of a set of readings from the simulated dataset with 8 features, while Fig. 2(c) and (d) display the grayscale and jet colormap representations for the real dataset with 4 features.

3.3. Definition of abnormal energy consumption using micro-moments

Data annotation is essential for applying supervised DL models and defining normal and abnormal energy consumption patterns. To that end, a micro-moment quantization is performed in recorded energy time series, where five energy micro-moment classes are defined. Typically, an energy micro-moment represents a daily intent-driven moment of user energy consumption actions. In this regard, for each appliance data, energy consumption footprints are split into: "class 0 - good usage": represents power consumption that is less than 0.95% of maximum active consumption rate (in watts); "class 1 - turn on a device"; "class 2 - turn off a device"; "class 3 - excessive consumption": refers to power consumption that more than 0.95% of maximum active consumption rate; and "class 4 - consumption while outside": deals with the abnormal energy consumption of an ensemble of devices, e.g., fans, air conditioners, televisions, light lamps, desktops/laptops, etc. Typically, with these devices, if the consumer is present during their operation, its energy consumption is considered normal; otherwise, it is regarded as abnormal.

Table 2 outlines the definitions of energy micro-moment classes adopted in this framework to annotated energy consumption datasets used to validate developed CNN-based ADEC models.

It is worth noting that the last two categories are responsible for wasting large amounts of energy. Thus, detecting these anomalous behaviors is of utmost importance before providing end-users personalized recommendations to correct their energy consumption behaviors. In doing so, a mobile app can be developed to provide end-users with real-time notifications and recommendations about their energy consumption patterns. On the other hand, the five micro-moment classes are extracted based on analyzing the occupancy profile (O) and power consumption (P) of each device in reference to the device active consumption range (DACR), device operation time (DOT), and device standby power consumption (DSPC). The proposed methodology used to extract micro-moment features (M^2F) over time is summarized in the following steps:

- **Step 1. Micro-moments definition:** power consumption readings p of an appliance and occupancy patterns O collected at a sampling rate t are recorded and stored in the dataset's backend server. Then, the appliance operation parameters are called, including $DACR$, DOT, and $DSPC$. Table 3 presents an example of different appliance parameter specifications used in the rule-based algorithm to extract power consumption micro-moments.
- **Step 2. Rule-based micro-moment extraction:** a rule-based algorithm is proposed to extract the micro-moment class of each power observation p(t) as explained in Algorithm 1.

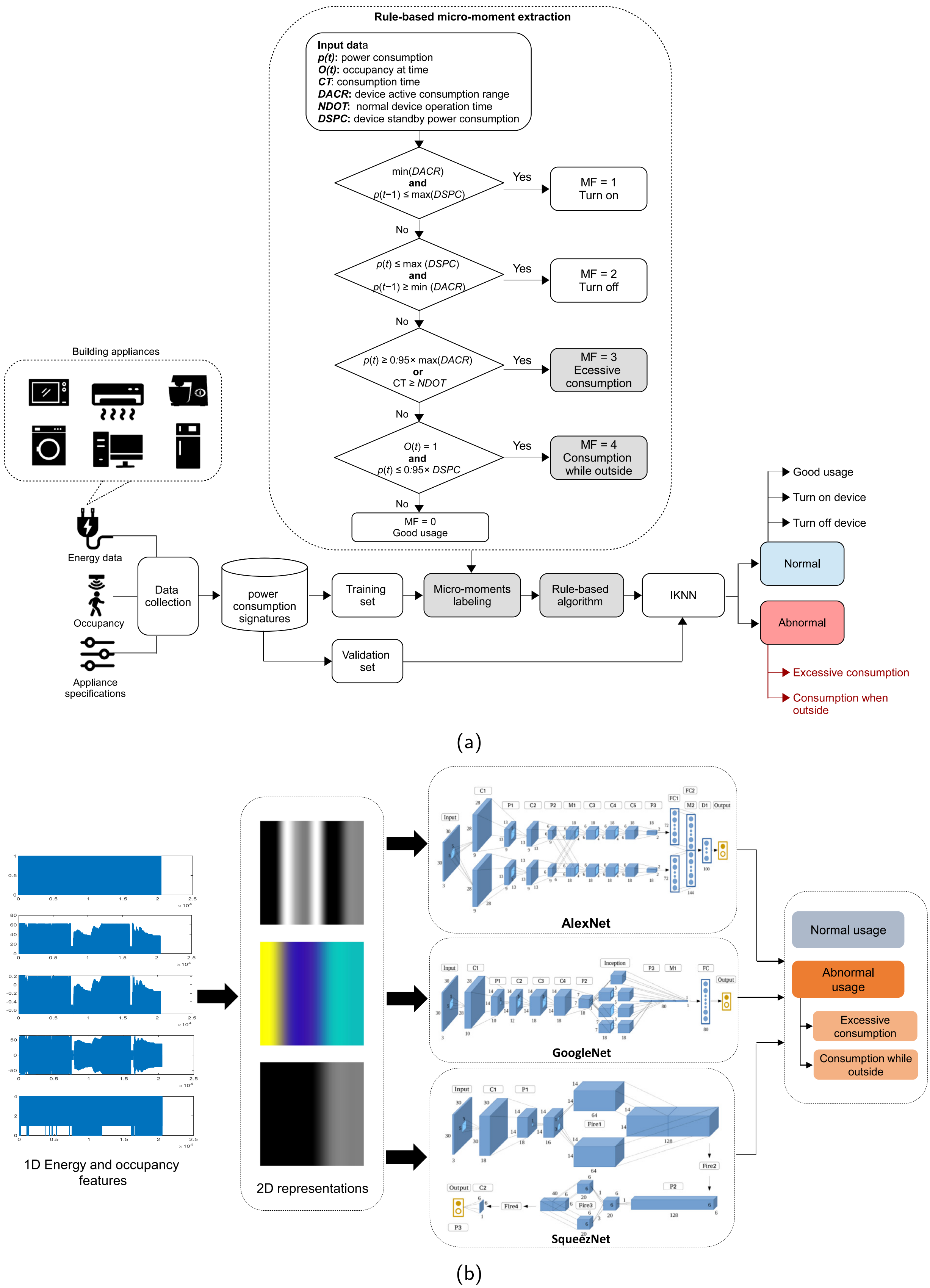

Fig. 3. Flowchart of the proposed ADEC based on time-series analysis: (a) ADEC using 1D signal analysis, (b) ADEC using 2D signal representations.

Table 2
Micro-moment classes definition and description for anomaly detection.

#	Class	Micro-moment description
0	Good consumption	Consume less than 95% of max. active consumption
1	Turn on	Switch on an appliance
2	Turn off	Switch off an appliance
3	Excessive consumption	>95% of max. active consumption
4	Consumption while outside	User not present while energy is consumed by an appliance

Algorithm 1: CNN Activations as Features to ML Models.

Result: classify(MLmodeltrain(features),test_value)
1. Label energy time-series data using a rule based algorithm as follows:

while $t \leq N$ **do**
  if $P(t) \geq min(A)$ **and** $P(t) \leq 0.95 \times \max(A)$ **then**
    MF(t) = 0 (Good usage) ;
  else if $P(t) \geq \min(A)$ **and** $P(t\text{-}1) \leq \max(S)$ **then**
    MF(t) = 1 (Turn on device) ;
  else if $P(t) \leq \max(S)$ **and** $P(t\text{-}1) \geq \min(A)$ **then**
    MF(t) = 2 (Turn off device) ;
  else if $P(t) \geq 0.95 \times \max(A)$ *or* $T_M(t) \geq \max(T)$ **then**
    MF(t) = 3 (Excessive consumption) ;
  else
    if $O(t) = 0$ **and** $P(t) \geq 0.95 \times \max(S)$ **then**
    MF(t) = 4 (consumption while outside) ;
  end
end

2. Convert energy time-series into N grayscale images, where l is the last fully connected layer of the model and x represents the model, with 1 representing model 1, 2 representing model 2, and 3 representing a combination of both.
3. Extract deep features to identify the types of abnormalities as follows:

while $t \leq N$ **do**
```
    case 1: while (i<l){
        features=[model_1(i)];
        }
      break;
    case 2: while (i<l){
        features=[model_2(i)];
        }
      break;
    case 3: while (i<l){
        features=[model_1(i);model_2(i)];
  }
      break;
```
end

4. classify (ML_model_train(features), micro-moment_labels)

3.4. Direct application of CNNs models

In this work, we represent the sensor readings derived from the relevant datasets after data annotation into time-series images for transfer learning. This is done by creating a matrix representation of the sensor readings and normalizing the values. After this, the images are concatenated in three dimensions to create an RGB format and converted into grayscale or a jet colormap array with 128 colors. Both representations will be examined for performance comparison purposes. Fig. 3 portrays the flowchart of the proposed approach.

Moreover, Algorithm 1 explains in detail the overall steps conducted to classify energy consumption footprints after transforming them into 2D representations.

Once the images are organized into specific folders, these are resized into the relevant image size requirement of the pre-trained model through bi-cubic interpolation coupled with antialiasing. These are then fed into the NN classifier for a 5-level classification training. In this work, we compare and investigate the performance of three pre-trained models, including AlexNet (Krizhevsky et al., 2012), GoogleNet (Szegedy et al., 2015), and SqueezNet (Iandola et al., 2016). A summary of information regarding these models is presented in Table 4.

Table 3
Power consumption specifications for different home appliances (Himeur et al., 2020b).

Appliance	DOT	DACR (W)	DSPC (W)
Air conditioner	15 h 30 min	1000	4
Microwave	1 h	1200	7
Oven	3 h	2400	6
Dishwasher	1 h 45 min	1800	3
Laptop	12 h 42 min	100	20
Washing machine	1 h	500	6
Light	8 h	60	0
Television	12 h 42 min	65	6
Refrigerator	17 h 30 min	180	0
Desktop	12 h 42 min	250	12

Table 4
Pre-trained model comparison.

Year	Model	Size	Layers	Error rate (%)	Parameters (million)
2012	AlexNet	277 × 277	8	15.3	60
2015	GoogleNet	277 × 277	22	6.67	7
2016	SqueezeNet	277 × 277	18	–	1.2

3.5. Transfer learning and hyper-parameter and layer variation

This section describes the proposed transfer learning methodology and the impact of hyper-parameter and layer variation on the performance of the proposed solution.

3.5.1. Transfer learning

Transfer learning has gained wide popularity in recent years due to its ability to provide adequate accuracy and performance at a significantly lower training time than a model trained from scratch (Kandel and Castelli, 2020). By definition, transfer learning in CNNs refers to re-using the parameters and framework of a previously trained model for a related application (Kandel and Castelli, 2020). In the case of this work, we re-use pre-trained models such as AlexNet (Krizhevsky et al., 2017), GoogleNet (Szegedy et al., 2015), and SqueezeNet (Iandola et al., 2016) for direct transfer learning applications. These models were previously trained using the ImageNet image classification dataset, which comprises 1.28 million images divided into 1000 classes. A summary of basic information regarding these models is provided in Table 5.

Nonetheless, since the pre-trained models are usually trained on large datasets, these models are often unnecessarily large. They can significantly be scaled down depending on the number of classes and data of the current application. This technique is known as hyper-parameter and layer variation, which will be discussed further in the following sub-section.

3.5.2. Hyper-parameter and layer variation

As previously mentioned in Section 3.2, the main aim of hyper-parameter and layer variation is to scale down the size of a pre-trained NN model based on a specific application for which it is used without

Table 5
General comparison summary between pre-trained CNN models (Copiaco et al., 2021).

Model	Year	Size (MB)	Input size	Layers	Parameters	5% ER
AlexNet (Krizhevsky et al., 2017)	2012	227	227 × 227	8	62.3 mil	16.4
GoogleNet (Szegedy et al., 2015)	2014	27	224 × 224	22	4 mil	6.70
ResNet (He et al., 2016)	2015	167	224 × 224	101*	25 mil	3.57
Inception-ResNet (Szegedy et al., 2017)	2017	209	299 × 299	164*	55.9 mil	–
Xception (Chollet, 2017)	2016	85	299 × 299	71	22.9 mil	–
SqueezeNet (Iandola et al., 2016)	2016	5.2	227 × 227	18	1.25 mil	–
VGGNet (Simonyan, 2014)	2014	515	224 × 224	41*	138 mil	7.30
LeNet (LeCun et al., 1998)	1998	–	32 × 32	7	60000	28.2

negatively affecting the overall system performance. This is done to gain advantages in time and resource requirements, which are factors that should also be considered when developing a usable system, alongside accuracy.

In this work, we mainly utilize MAlexNet-40 (Copiaco et al., 2021), a 40-layer variant of the AlexNet pre-trained network with fewer hyper-parameters. This is originally developed by Copiaco et al. (2021) for home monitoring purposes using Continuous Wavelet Transform (CWT) scalogram image representations of audio signals as the main medium. This was established by increasing the number of convolutional layers while decreasing the number of hyper-parameters to account for a sufficient balance.

Result comparisons in the weighted F1-score served as the main grounds for decision-making on the variations made. For the experiments conducted in this work, MAlexNet-40 is used in two ways: (i) as a traditional transfer learning pre-trained model and (ii) as a CNN activations extractor. For both techniques, aside from the weighted F1-score, time and resource requirement measures play an important role in determining the suitability of this technique for the selected application. Hyper-parameter varied models are often made to specifically suit what they are developed for. Hence, they possess a different advantage of adaptability and flexibility than more extensive networks trained on large datasets.

It is important to note that in this work, we do not necessarily aim to develop a specifically-suited hyper-parameter varied model. Instead, the objective of conducting this experiment is to assess the suitability of this method for this specific application.

3.6. CNN activations as features to ML models

The utilization of NN models as a feature extraction technique is another method that arose in recent years (Chen et al., 2016; Toğaçar et al., 2020). Nonetheless, this technique's evidence remains limited, particularly for building energy consumption applications. Using CNN activations as features of ML techniques proposes possible combined advantages of the two methodologies.

For instance, CNNs are known for providing adequate computational efficiency (Gu et al., 2018). Further, it yields a high accuracy, particularly for data that possess a spatial relationship. On the other hand, there are also significant advantages found in ML techniques. For example, the support vector machines (SVM) classifier consistently returns high accuracy, even for unstructured data (Dhiman et al., 2021).

Hence, this work aims to merge the advantages of CNNs and ML methodologies by using the CNN model as a feature extractor and integrating this with ML through different techniques of fusion, including early fusion, joint fusion, and late fusion, as per the comparison diagram provided in Fig. 4.

It is important to note that the diagrams shown in Fig. 4 represent the combination of two features or two types of images. As observed, in early fusion type I, different features are concatenated before being sent into a model for classification. The second type of early fusion involves varying the second type of feature to an extent and sending it in the same model as the first type. Although this is a fairly simple type of fusion that does not require a complex design, it is not equipped with the flexibility to integrate features at multiple levels of abstraction (Qiu et al., 2018). Another type of fusion is joint fusion, which falls under two categories. The first category involves extracting activations individually for all features concerned. These activations are then concatenated and sent to a model for training, while the second category does the same, but solely for the first feature. The second feature is sent to the model directly without extracting activations. This method provides advantages in terms of flexibility. Further, it does not require training multiple models, which saves training time and resource requirements (Christlein et al., 2015). Similarly, it is also equipped with advantages in learning more compatible features at each modality, provided that it uses CNNs to extract activations (Gholamalinezhad and Khosravi, 2020; Kelly and Knottenbelt, 2015). Nonetheless, this type of fusion requires a large number of training data for better accuracy. Finally, late fusion utilizes aggregation subsequent to concatenating the CNN activation modalities extracted for the individual features. Although this methodology does not require a large number of data for training, it cannot model features from varying modalities nor learn the compatibility of features extracted from each modality as much as the joint fusion does.

For these reasons, we will particularly focus on early fusion and joint fusion in the scope of this work. Several ML and CNN models will also be compared and paired. The optimum methodology is then identified through the highest accuracy and the least time and resource requirements.

4. Experimental results

This section details the results gathered by applying the methodologies discussed in the previous section. Since this work aims to find the optimal methodology for the selected application, techniques are mainly compared in terms of their weighted F1-scores. The F1-score is considered to be the harmonic mean of the recall and precision, allowing a balanced representation between the two metrics regardless of imbalanced data.

In addition to this, several other reliable metrics are considered, such as specificity, precision, recall, and accuracy. The recall, which is also known as sensitivity, focuses on the number of True Positives in each class. The specificity, however, focuses on the number of True Negatives correctly identified. Reporting our results on these four metrics allows us to represent the system performance from multiple perspectives depending on the priority level. For example, if detecting positive cases correctly is the main goal, then the recall can report an estimated performance on this. The same is true with the specificity for negative predictions. Regardless, displaying comparable figures between the four metrics show the robustness of the overall system in all cases.

A visual representation of the system performance is also given through the confusion matrix, which visually displays the ratio of True and False Positives, as well as True and False negatives under each category. Finally, the time and resource requirements ratio is

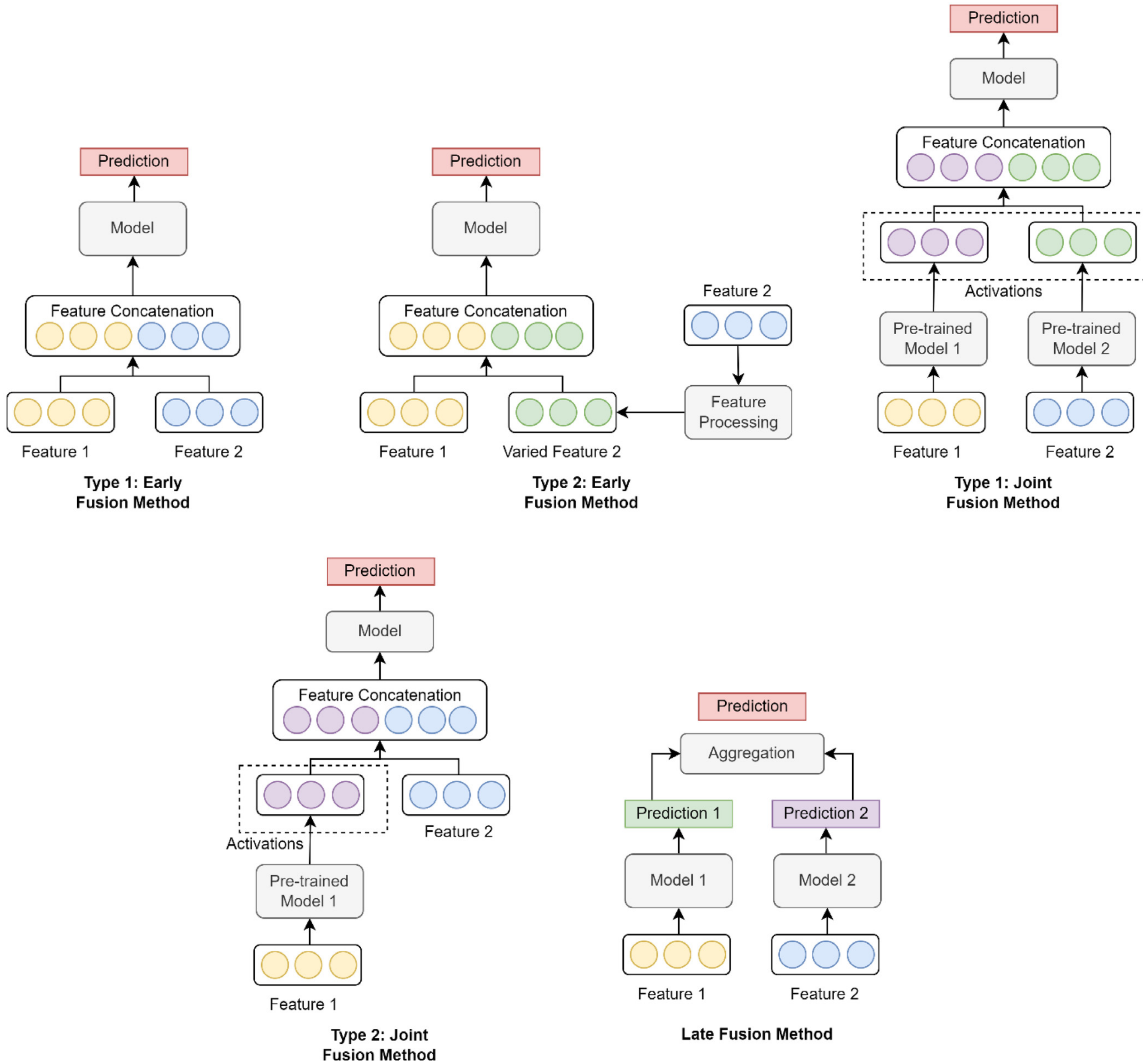

Fig. 4. The different fusion Strategies using DL.

computed for the methods being compared, provided that the same system specifications are used to generate the results.

The experimental work begins by comparing different pre-trained models and image representations through the application of direct transfer learning. This would help identify the optimum image representation technique, which will be used throughout the rest of the experiments. Further, comparing different pre-trained models will also provide a benchmark for the rest of the experiments to compare against. Fig. 5 displays the comparison of the grayscale, jet-128, and non-scaled image representations, as well as AlexNet, GoogleNet, and SqueezeNet pre-trained models, using the SiD dataset. The data is utilized at an 80–20 split in favor of the training set.

As observed, both AlexNet and GoogleNet have returned a comparable performance for classification. Hence, both models will be considered CNN activation methods in the succeeding experiments. Further, for all pre-trained models compared, the grayscale image representation yielded the highest F1-score. For this reason, the rest of the experiments will utilize this image representation as input.

4.1. Neural activations and ML: Combining human brain comprehension with statistical comprehension

This section explores the applicability of combining the advantages associated with CNNs and ML techniques. This leads to the development of an innovative approach that utilizes activations extracted from CNN models as features of an SVM classifier, as portrayed in Fig. 6. This begins by feeding the grayscale image representations as features to the selected NN. The network is then trained to the last fully connected layer, where activations are extracted. These activations contain information analyzed by the CNN architecture, which can help provide higher accuracy to the ML prediction. Table 6 displays the detailed results yielded when using AlexNet as a CNN activation extractor and using these as features to a Linear SVM classifier. In contrast, Table 7 displays the results for GoogleNet.

As per Tables 6 and 7, a substantial improvement was observed in the results, which proves that there is indeed important information that can be gathered by the CNNs' comprehension of the inputs given.

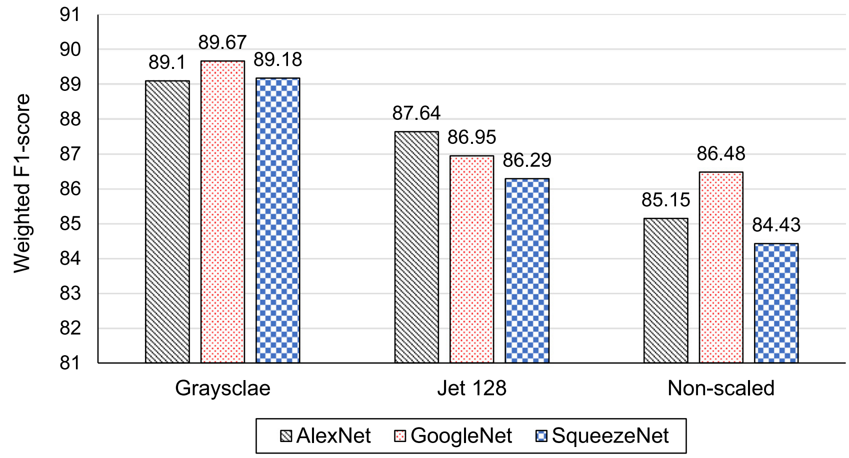

Fig. 5. Weighted F1-score comparison for the SiD dataset.

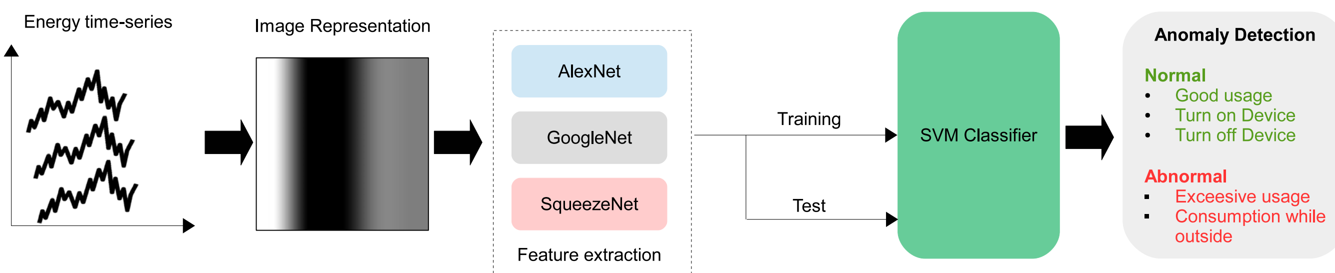

Fig. 6. Flowchart of the final approach implemented to detect energy consumption anomalies.

Table 6
Results of combining AlexNet Activations with Linear SVM.

Micro-moment classes	Train	Test	TP	FP	FN	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
0	47540	11885	11580	841	308	97.43	93.23	97.41	95.27
1	6224	1556	1110	243	446	71.34	82.04	71.34	76.31
2	6223	1556	1127	94	429	72.43	92.30	72.43	81.17
3	5074	1269	939	132	330	74.00	87.68	74.00	80.26
4	19034	4759	4699	263	60	98.74	94.70	98.74	96.68
TOTAL	84095	21025	19455	1573	1573	92.53	92.33	92.52	92.24

Table 7
Results of combining GoogleNet Activations with Linear SVM.

Micro-moment classes	Train	Test	TP	FP	FN	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
0	47540	11885	11700	904	189	98.44	98.41	92.83	95.54
1	6224	1556	1037	133	519	66.65	66.65	88.63	76.08
2	6223	1556	1120	85	436	71.98	71.98	92.95	81.13
3	5074	1269	958	114	331	75.49	75.49	89.37	81.85
4	19034	4759	4696	282	63	98.68	98.68	94.34	96.49
TOTAL	84095	21025	19511	1518	1518	92.80	92.78	92.66	92.41

Due to this, other ML techniques are also tested and compared against the Linear SVM, the results of which are shown in Fig. 7. It is also important to note that the Recall metric shows better performance when compared to the other metrics in the majority of the classes. This suggests that the correct identification of that class (True Positive) is more commonly encountered, as opposed to the misidentification of the other classes in question. This characteristic is ideal for detecting anomalies, as true positives are prioritized over false negatives.

Having found the Linear SVM to be the optimum ML technique for this application, we continue exploring the different fusion methods, particularly the joint fusion method, discussed in Section 3.5.2 using this model. Table 8 enlists the different combinations made, along with the weighted F1-scores yielded from the comparisons.

Table 8
Fusion technique experimental results.

Input 1	Model 1	Input 2	Model 2	ML Technique	F1-score
Grayscale	AlexNet	Grayscale	GoogleNet	Linear SVM	93.63%
Jet-128	AlexNet	Jet-128	GoogleNet	Linear SVM	92.09%
Grayscale	AlexNet	Jet-128	AlexNet	Linear SVM	93.36%
Grayscale	GoogleNet	Jet-128	GoogleNet	Linear SVM	93.28%

As observed, applying the fusion method presented benefits in the accuracy of the overall system. The advantages associated with this technique can be justified by the fact that CNNs are structured in terms of neurons, which is similar in functionality to human brain

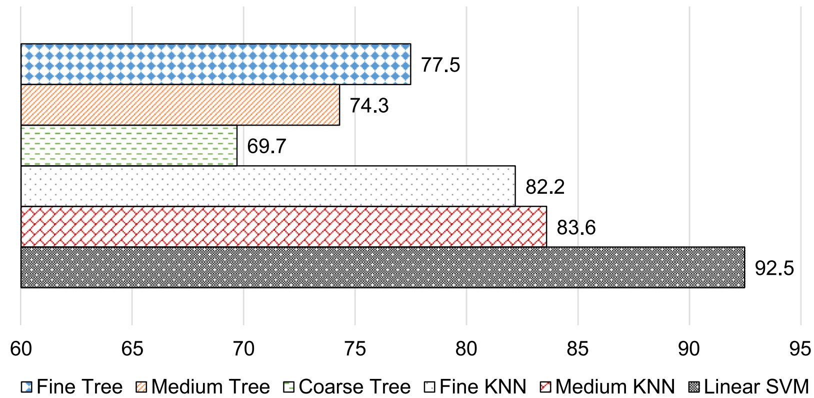

Fig. 7. Weighted F1-score comparison different ML techniques, using AlexNet-extracted activations as features.

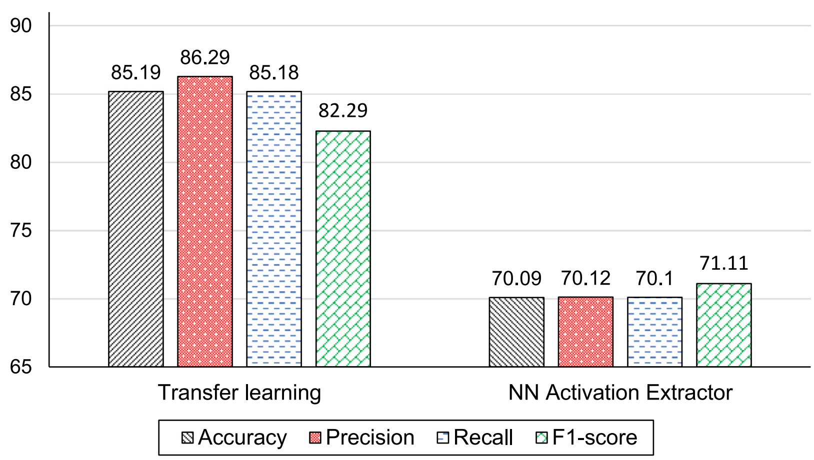

Fig. 8. Results of using MAlexNet-40 for transfer learning and activation extraction.

comprehension. Using two different inputs or two different models in the methodology allows the system to think in a similar manner to two different brains that can provide varying perspectives on a specific application. For this reason, it can be deduced that this technique could identify deeper-level features that can help stimulate the statistical-based ML model to yield higher accuracy.

4.2. Effects of a hyper-parameter varied model

Given the positive findings reported in the previous sub-sections, this sub-section presents the analysis of the applicability of hyper-parameter and layer variation on CNN models for the selected application. A hyper-parameter varied model is usually tailored explicitly for the chosen application. The major benefit of using this technique is an improved resource requirement, provided that varying the hyper-parameters used in a CNN architecture can significantly scale down the model's size. Nonetheless, developing your hyper-parameter varied model is often time-consuming since developing a specific model is done through a trial-and-error process.

Hence, in this experiment, we will use the MAlexNet-40 (Copiaco et al., 2021), initially developed to suit a 10-level classification system of sound classes using Continuous Wavelet Transform scalogram RGB image representations. This is a variation of the AlexNet, which scaled the size down from 220 MB to a mere 14 MB while providing the authors with higher accuracy.

It is important to note that this experiment aims solely to test out the time and resource advantages offered by the hyper-parameter varied model compared to our current optimum technique, which involves the use of CNN activations as features of the Linear SVM model. We test the hyper-parameter varied model in two ways, both of which utilize the grayscale image representation as the primary input type:

- Direct transfer learning with MAlexNet-40.
- Using MAlexNet-40 as a CNN activation extractor for the Linear SVM.

Fig. 8 displays the results of these techniques, compared in four weighted metrics, including accuracy, precision, recall, and F1-score.

As observed, although the hyper-parameter varied model gave reasonable results for direct transfer learning, it did not provide promising results for an activation extractor. Either way, the current top methodology still exceeds the transfer learning method by over 10%. Hence, to assess whether it would be beneficial to develop a specific hyper-parameter varied model for this application, the time and resource requirements were then looked at. Table 9 reports the findings with regard to this experiment. Time readings were taken using an Intel(R) Core(TM) i7-8550U CPU at 1.80 GHz, 2.00 GHz processor.

It is important to note that Table 9 reports the time extractions for the entire database. As observed, the results infer that although a higher accuracy can be attained by extracting features from two pre-trained models, the time it takes to extract those features increases accordingly. Nonetheless, it is evident that although GoogleNet and MAlexNet-40 are smaller in size compared to the AlexNet, the time it takes to extract activations is not necessarily shorter, but rather, using a hyper-parameter varied model only shortens the training time of the SVM model. Since the SVM model will be exported for use after training, a lower training time is not necessarily relevant for measuring the performance of the overall model. For this reason, we conclude the experiments with the joint fusion of AlexNet and GoogleNet extracted activations from Grayscale images as features to the Linear SVM classifier as the top methodology, yielding an F1-score of 93.63%. T_S Moreover, Fig. 9 portrays the confusion matrices of the implemented models,

Table 9
Time and resource requirements analysis.

Time extraction report				SVM training time Report			
Model	Layer	Time (s)	Time (h)	CNN Size	Architecture	Layers	Training Ratio
GoogleNet	loss3	8426	2.341	27 MB	DAG	144	8x
AlexNet	fc8	4628	1.285	227 MB	Series	25	5x
Both models	N/A	13000	3.611	N/A	N/A	N/A	N/A
MAlexNet-40	fc38	4039	1.122	14 MB	Series	40	1x

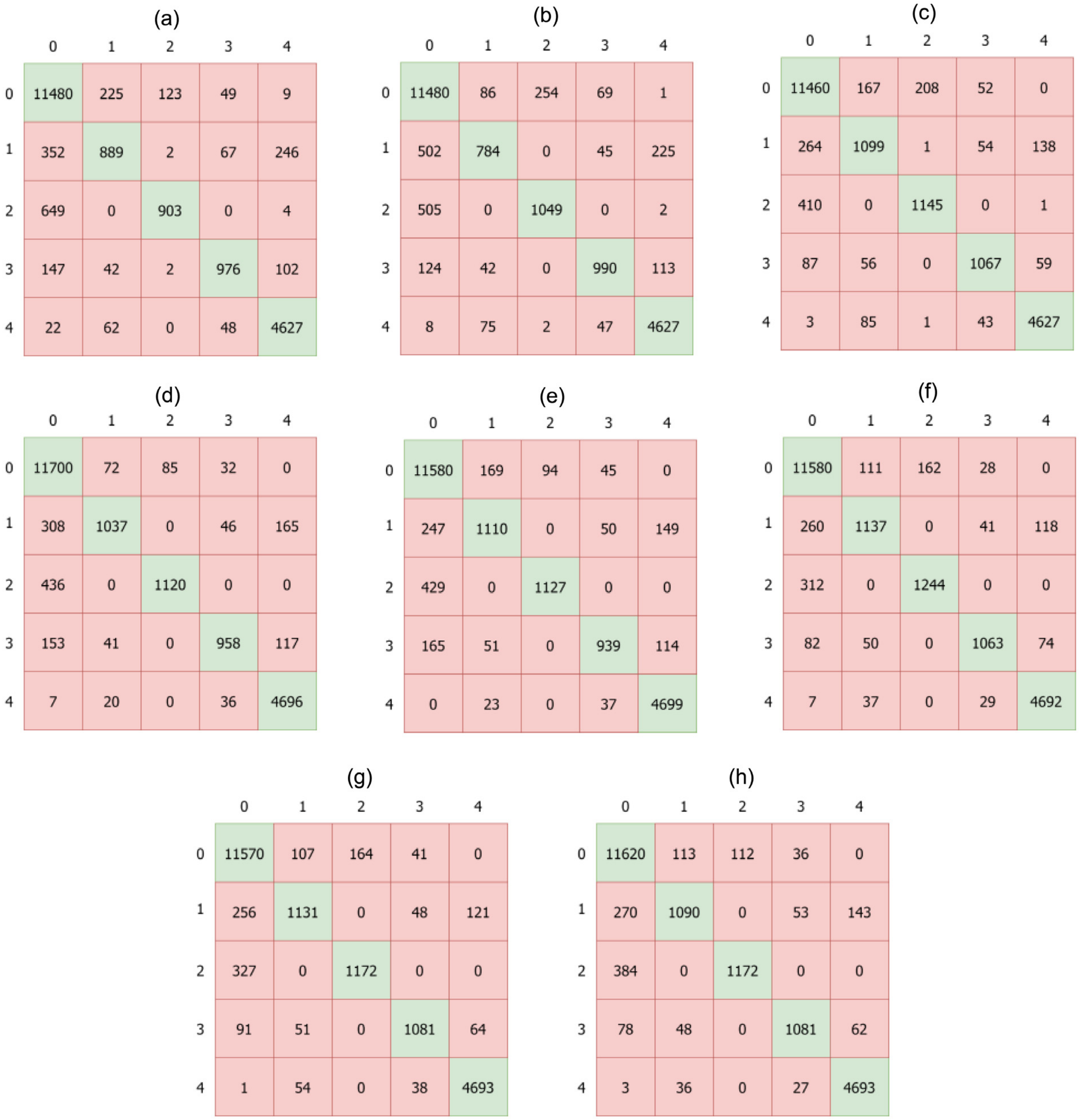

Fig. 9. Confusion matrices of the implemented models: (a) Jet_GNetSVM, (b) Jet_ANetSVM, (c) Jet_ANetGNetSVM, (d) RS_GNetSVM, (e) RS_ANetSVM, (f) RS_ANetGNetSVM, (g) RSandJET_ANetSVM, and (h) BEST_RSandJET_GNetSVM.

including (a) Jet_GNetSVM, (b) Jet_ANetSVM, (c) Jet_ANetGNetSVM, (d) RS_GNetSVM, (e) RS_ANetSVM, (f) RS_ANetGNetSVM, (g) RSandJET_ANetSVM, and (h) BEST_RSandJET_GNetSVM.

4.3. Correlation analysis

To justify the use of pre-trained 2D CNN models as features from an SVM, a correlation analysis has been conducted to check the correlation rates between (i) energy time-series from the same class and from different classes and (ii) images that belong to the same class and those from different classes. Accordingly, Fig. 10 presents the correlation results obtained on SiD and DRED datasets. As presented in Fig. 10(a), the correlations between signals time-series of the same class (in diagonal) were high but also between signals from different classes. This can result in increasing the false-positive rate. However, in Fig. 10(b), it is clear that after transforming energy time-series into images, only

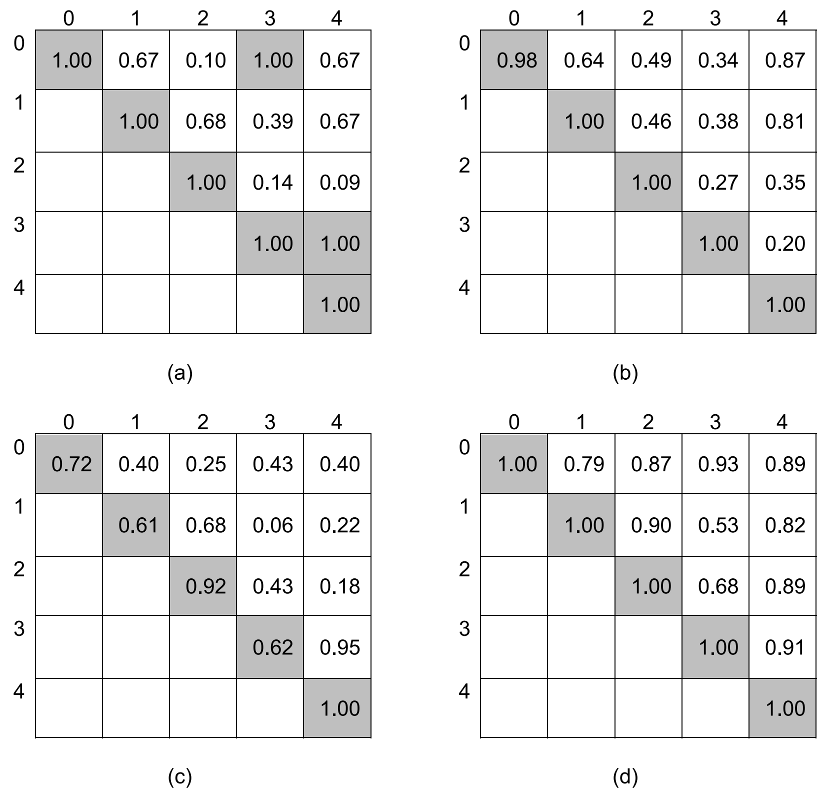

Fig. 10. Correlation matrices measured between (a) energy time-series signals from SiD, (b) images extracted from SiD; (c) energy time-series signals from DRED; and (d) images extracted from DRED.

the correlations between images from the same class (in the diagonal) have been kept high. By contrast, the correlations between images from distinct classes have been reduced or maintained at 87%, which can help discriminate between them easily when using the SVM classifier. Moreover, under DRED, it can be shown that after transforming the energy time-series into images (10(d)), the correlations between images from each same class have been increased to reach 100%. This was not the case in Fig. 10(c), where the correlation rates were much lower.

Overall, this study has demonstrated that transforming energy time-series into images can help increase the correlation between images from the same class while increasing the discrimination between images from different classes. Typically, this has resulted in better detecting and classifying energy anomalies after applying pre-trained CNN as feature extractors and SVM as a classifier.

4.4. Comparison with the state-of-the-art

A comparative evaluation study is conducted to prove the efficiency of the proposed ADEC based on DTL and energy time-series images. Typically, the performance of the proposed method in terms of accuracy and F1-score has been compared with the studies presented in Himeur et al. (2020b) and Himeur et al. (2021b). The former uses a 1D-DNN model and the micro-moment concept to detect abnormal energy consumption. By contrast, the latter has relied on using an improved K-nearest neighbors (KNN) classifier and the micro-moment paradigm. Table 10 presents the anomaly detection accuracy and F1-score obtained by these techniques.

While it is clear from Table 10 that DRED presents less challenge in detecting energy consumption anomalies than SiD, the proposed method performs better than the other techniques based on 1D-DNN and IKNN. On the other hand, the superiority of our approach is significant under SiD, where 2.68% and 2.2% accuracy improvements have been reached compared to Himeur et al. (2020b) and Himeur et al. (2021b), respectively. Additionally, the improvements in terms of the F1-score have attained 3.39% and 4.53% in comparison with Himeur et al. (2020b) and Himeur et al. (2021b), respectively.

5. Conclusion

In conclusion, this paper innovates in detecting energy consumption anomalies using energy time-series images by presenting the first study investigating such an idea to the best of the authors' knowledge. In this regard, 1D energy time series were transformed to 2D images to (i) ease the use of pre-trained 2D CNN models, (ii) provide more possibilities of encoding the features as each sample is surrounded with 8 samples, (iii) simplify the interpretation of the anomaly classification process. More specifically, this work assessed the applicability of transfer learning using CNN-extracted activations and hyper-parameter varied models for ADEC in buildings.

Moreover, experiments involving the different levels of feature fusion were explored, which helped confirm the linear relationship between anomaly detection accuracy and fusion techniques. Additionally, aside from traditional transfer learning, the concept of combining the advantages of ML and DL techniques was also explored from the experimental point of view. Accordingly, pre-trained CNN models, such as AlexNet and GoogleNet were used as feature extractors the anomaly classification was completed using SVM. In this line, the effects of utilizing a hyper-parameter varied model both as a feature extractor and a classifier were investigated in terms of both time and resource requirements. The top methodology provides an F1-score of 93.63%, involving the use of CNN activations extracted from gray-scale images using AlexNet and GoogleNet pre-trained models as features of the Linear SVM classifier. Furthermore, a comparative study has been conducted with the state-of-the-art ADEC methods, in which the proposed methods has shown clear superiority in terms of different evaluation criteria.

All in all, this framework demonstrated that combining energy time series images and image classification capabilities of pre-trained

Table 10
Performance comparison of the proposed method with the state-of-the-art.

Work	Model description	DRED		SiD	
		Accuracy (%)	F1-score (%)	Accuracy (%)	F1-score (%)
Himeur et al. (2020b)	1D DNN + micro-moments applied on energy time-series	99.29	99.60	93.43	90.24
Himeur et al. (2021b)	IKNN + micro-moments applied on energy time-series	99.71	99.77	93.91	89.10
Proposed	2D pretrained CNN applied on energy time-series images	99.91	99.89	96.11	93.63

CNN models can provide promising classification performance while eliminating manual preprocessing steps, including noise elimination, feature extraction, and feature selection. On the other hand, the research outcome of the study opens new doors for more investigations regarding the use of 2D pre-trained CNN models for anomaly detection of time series and related applications, such as occupancy detection in buildings, indoor air quality monitoring, and comfort optimization. Moreover, this work can be improved from different perspectives. However, this study provides some minor limitations that can mainly be related to using supervised learning, which necessitates data labeling before training pre-trained CNN models. However, this is related to all ML/DL models based on supervised learning and not unique to our solution. Lastly, future work will rely on developing a complete energy-saving solution for the University of Dubai campus based on the ADEC approach proposed in this paper. This will be possible by (i) adding a recommendation generation module, (ii) using the Home Assistant mobile app to receive explainable recommendations and visualize energy usage in real-time, and (iii) implementing the overall system on edge devices to preserve privacy and improve security.

CRediT authorship contribution statement

Abigail Copiaco: Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Yassine Himeur:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Abbes Amira:** Funding acquisition, Writing – review & editing, Project administration, Supervision. **Wathiq Mansoor:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Fodil Fadli:** Funding acquisition, Writing – review & editing, Project administration, Supervision. **Shadi Atalla:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Shahab Saquib Sohail:** Conceptualization, Formal analysis, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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