A Comprehensive Investigation into the Application of Convolutional Neural Networks (ConvNet/CNN) in Smart Grids

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Abstract**—** The convolutional neural network methodologies have been a fundamental deep learning solution to smart grid applications. It is essential to investigate and evaluate the progress of this method in the smart grid. Consequently, a comprehensive investigation with the aid of PRISMA had been conducted. The PRISMA standard queries including the convolutional neural networks and its abbreviation forms of ConvNet or CNN reveal a significant increase in the popularity of this deep learning method in smart grid applications. This research identifies 2200 pieces of literature in the field. After considering the PRISMA guideline the most relevant and fundamental application had been reduced to 46 documents where the single and hybrid methods had been identified. The investigation showed that hybrid methods delivered a better performance with higher accuracy. It is expected that more hybrid methods will have emerged in the smart grid application.

Keywords— *Convolutional Neural Network, Smart Grid, PRISMA, Hybrid Methods.*

I. Introduction

Recent developments in cutting-edge monitoring, information, and communication technology used in the smart grid, intended to make energy delivery more dependable, economical, and sustainable, will enable electric power systems to respond to various customer demands more effectively [1]. Daily load forecasting is emerging as a very interesting area in the smart grid as it covers the daily load curve for residential and commercial electricity usage. This includes the dynamic price incentives on the demand responses [2]. This helps to take into account the main cyclical features in the power system, like holidays and special days adjustment, and temperature effects that directly influence the electricity demand [3]. Dynamic pricing aids in lowering the system's peak load [4]. Information technology, which enables local control, distributed energy resource collaboration, and global energy markets, is one of the key elements of smart grids. Our power system is projected to become more reliable, "green," and efficient thanks to smart grids, a challenge that the automobile sector could only meet by integrating digital controls into engines [5]. One application area that is still developing is smart grids. The last ten years have seen the emergence of numerous smart grid projects using various multi-agent system interpretations as new control concepts. Although the term "agent" has several theoretical definitions, there is a lack of practical comprehension that may be remedied by clearly separating agent technologies from other cutting-edge control technologies [6]. Furthermore, the communication systems still need to improve in the smart grid to integrate generated power from solar, wind, and other renewable energy resources [7].

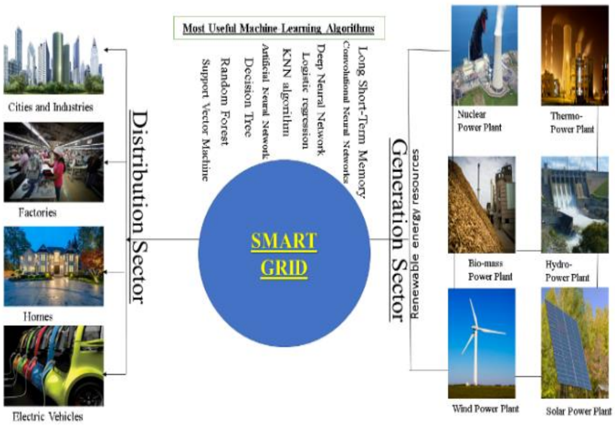

Fig. 1 Short-view of smart grid.

Recently, machine learning approaches like Extra Tree, Least Squares Support Vector Machine, and Gaussian Process Regression have significantly improved several science and technology disciplines. This can be used to forecast whether underground natural gas storage sites will be available in time to support sustainable development goals [8]. The random forest, decision tree, support vector regression, and artificial neural network algorithms can be employed to determine the pore pressure. This can evaluate the geomechanically parameters of the reservoir. It is essential for developing oil and gas fields [9]. An artificial electric field algorithm that climbs hills can be used to track a photovoltaic system's greatest Power [10]. Powerful models like AlexNet may produce results with high accuracy on even the most challenging datasets [11]. Taguchi and response surface method can be used to remove the malachite green and auramine-O by NaX nano zeolites from the polluted water [12]. Using random forest, gradient boosting model, extreme gradient boosting, and their ensembles, it is possible to map the implications of flood threats. These are influenced by climate change and changes in land use. [13]. Three types of artificial neural network-based multi-layer perceptron can be used to predict the degree of dissolved oxygen [14]. The interval type-3 fuzzy logic systems, a specific instance of general type-2 fuzzy systems, serve as the foundation for dynamic fractional-order models [15]. Interval type-3 fuzzy logic is used to model each output of the system. This utilizes multiple first-order dynamic fractional order fuzzy systems [16]. Optimization methods like particle swarm optimization, genetic algorithms, artificial bee colonies, and backtracking search algorithms can be utilized to determine the ideal parameters of the smart grid [17]. For each of the six depth increases, the wavelet support vector regression improves performance in forecasting soil salinity [18].

The data-driven approaches have been enhancing the modeling quality in a variety of applications, including Pearson's correlation. This reveals strong positive connections between the number of the Covid-19 patients and the number of deaths caused by this pandemic [19]. To identify flood-prone areas, the methods boosted regression tree, parallel random forest, very randomized trees, random forest, and regularized random forest are helpful [20]. The ability of hybrid failure mode and effects analysis aids in overcoming several shortcomings in the use of traditional FMEA [21]. The multi-layer perceptron together with whale optimization techniques can be helpful to model a hybrid model which can predicts the wind speed [22]. The Bayesian artificial neural network and support vector machine algorithms are helpful for the accurate estimation of groundwater nitrate concentration [23]. The hybrid model's ability to capture maximum salinity values has been greatly improved by the hybridization of machine learning techniques. This is very crucial for the management of water resources [24]. The development of comparative research with multivariate discriminant analysis is used to evaluate the performance of two ensemble models, boosted regression trees and the random forest [25]. Scalability and the capacity to use noisy, nonlinear economic data patterns in conjunction with high-dimensional problems are two characteristics of deep reinforcement learning [26]. The efficacy of the deep learning neural network and particle swarm optimization method for predicting the susceptibility of gully erosion is 89% [27]. The nomadic people algorithm increases the soft computing models' accuracy and convergence speed [28]. The stability of photovoltaic/battery systems is ensured by a fractional-order control system. This is based on type-3 fuzzy logic systems under unknowable dynamics, fluctuating irradiance, and temperature [29]. With the best model fitting ability, LSTM produces more accurate findings. Additionally, Adaboost, Gradient Boosting, and XGBoost frequently compete fiercely for tree-based models [30]. The most effective models for identifying other sensitive areas' vulnerability to gully erosion are based on credal decision trees random forest, and kernel logistic regression [31]. At the provincial level, the deep neural network assists in managing a lot of supplementary data [32]. For modeling and uncertainty analysis of groundwater levels, the adaptive neuro-fuzzy interface system with the grasshopper optimization algorithm and support vector machine exhibits the best and worst results, respectively [33]. The best methods for estimating the solubility of acids in supercritical carbon dioxide are provided by the radial basis function artificial neural network, multi-layer perceptron artificial neural network, least squares support vector machine, and adaptive neuro-fuzzy inference system. This can help chemists and engineers forecast operational conditions in the sector [34]. The space syntax technique can be used to assess how spatial integration of urban settings affects the quality of physical activity [35]. The bootstrapping algorithm with the generalized additive model attains superior performance in terms of statistical measures for flood susceptibility prediction [36]. The radio duty cycles for false wakeups and idle listening are decreased using a quick clear channel evaluation method. This is done by using dynamic received signal strength indicator status check time and saves about 8% energy consumption [37]. The recurrent neural network and long short-term memory algorithms outperform stock market trends via continuous and binary data [38]. The DistBlockBuilding architecture is employed to handle risk-free and safe data transmission from one surface to another surface [39].

Smart grid applications had been embedded into the concept of a smart city with a wide range of applications, e.g., support vector machine algorithm-based model predicts the power and energy demand-supply consumption in smart grid to achieve smart city smartly [40, 43]. A new evolving machine learning algorithm helps to accurately intrusion detection systems in smart grids [41]. The Bagging classifier algorithm predicts the power consumption in a smart grid with 97.9% of accuracy [42]. The random forest-based model has outperformed by 10% as compared to other machine learning-based algorithms for theft detection datasets for benchmarking in the smart grid environment [44]. By increasing efficiency, the energy optimization method may reduce the delay rate to 40.3% while increasing real and expected cost analysis by 95% [45].

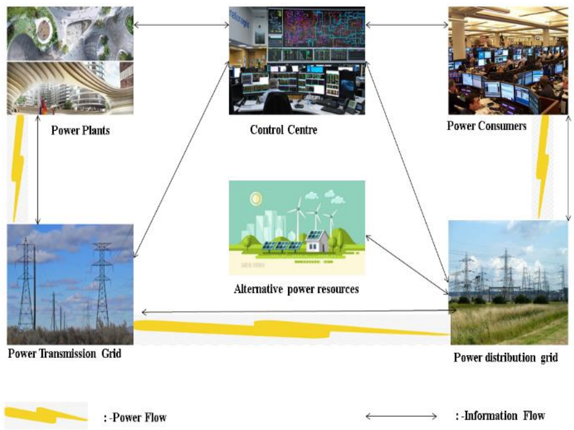

Fig 2. Need for machine intelligence in the smart grid.

Deep learning methods on the other hand work best on big datasets and learns from data. The relationships between input and output data and variables are well modeled using deep learning methods and deliver insight into comprehensive datasets. Smart grids incorporate a wide range of deep learning applications and methodologies. For instance, a the grained recurrent unit algorithm gives better result in smart grid cyber security audits, as compare to CNN-based long short-term memory algorithm [46]. The performance of a machine-learning-based ultra-lightweight data aggregation technique for smart grids that do not require a secret key to be retained for communicating with the aggregator is improved by employing collaborative learning [47]. Deep Neural Networks and Decision Tree classifiers perform better at managing risk in the smart grid's financial sector [48]. To increase classification accuracy and examine electricity theft in the smart grid, the outputs of the ML algorithms can be combined using the temporal convolutional network [49.50]. A deep learning framework estimates the solar generators' intra-hour output power interval. Also, it detects the data invasions in real-time and with pinpoint accuracy [51]. There are two primary phases to CNN's training for voice emotion recognition. To begin with, local invariant characteristics are learned using unlabeled data. It makes use of a sparse auto-encoder variant with reconstruction penalization. The second stage involves sending local invariant characteristics. This features extractor termed salient discriminative feature analysis. Using a brand-new objective function, this trains discriminative features that are sensitive to affect. Recognizing speech emotions promotes feature saliency, orthogonality, and discrimination [52]. The convolutional neural network methodologies have been a fundamental deep learning solution to smart grid applications. It is essential to investigate and evaluate the progress of this method in the smart grid. Consequently, a comprehensive investigation with the aid of PRISMA had been conducted. The PRISMA standard queries including the convolutional neural networks and its abbreviation forms of ConvNet or CNN reveal a significant increase in the popularity of this deep learning method in smart grid applications. This research identifies 2200 pieces of literature in the field. After considering the PRISMA guideline the most relevant and fundamental application had been reduced to 46 documents where the single and hybrid methods had been identified. The investigation showed that hybrid methods delivered a better performance with higher accuracy. It is expected that more hybrid methods will have emerged in the smart grid application. Unlabeled samples from the CNN training sets are trained using a sparse auto-encoder variant. This requires reconstruction penalization to learn local invariant features. CNN is a flexible and effective deep learning technique for understanding speech and emotion. The objective function promotes feature saliency, orthogonality, and discrimination for speech error recognition [53]. In comparison to deep neural networks, CNNs help reduce the speech recognition error rate on the TIMIT phone recognition and voice search large vocabulary tasks by 6%–10% [54]. However, CNNs frequently cannot be employed for object recognition jobs with real-time restrictions, where several predictions must be performed on sub-windows of a big input image. This is owing to the high model complexity [55]. CNNs can be used in a limited-weight-sharing method to more accurately simulate speech features [56]. A CNN to accurately predict image quality without a reference image [57].

The CNN had been proposed in the early 90s and it started to gain popularity in image and speech analysis by 2014. Today, CNN is used for a variety of purposes and in many different ways. For example, with 96.97% accuracy, the CNN classifier is designed to predict whether a lung lesion is malignant or not based on the features gathered. With an accuracy rate of 98.55. For identifying pneumonia, the ensemble classifier using support vector machines with radial basis functions and logistic regression classifiers performs well [58]. To detect coronavirus disease from chest X-ray imaging, an improved densely connected convolutional network method based on transfer learning can be used [59,60]. The efficiency of classifying the eight main personality qualities from text using integration of convolutional neural networks and Long Short-Term Memory. [61]. Due to its intelligence, effective learning, precision, and resilience in model development, deep learning is now a need [62]. Picture data processing is well suited to a multi-layer neural network architecture [63]. Convolutional neural networks enforce a local connectivity pattern in which each neuron only interacts with a tiny local subset of the neurons. This referred to as the local receptive field of the preceding layer. [64].

By introducing weight sharing across spectrum and time, CNN gives the model translational robustness to minor model changes. Additionally, CNNs frequently use pooling, which adds more translational and rotational invariance [65]. Using a CNN with automated speech recognition (ASR) training, identify speakers [66]. Key detection, chord detection, and genre and artist classification have all been tested using convolutional learning on music audio data. Aside from our first research, CNNs have never been used for the relatively low-level task of onset detection, despite the findings being promising [67]. Before delivering the picture patches to the DCNN for classification, they are first processed. A linear plane can be fit onto the image intensity as represented by

$$"ax + by + c = I" \tag{1}$$

where (x,y) is the location of the pixel, I is the intensity of the corresponding pixel, and a, b, and c are the fitting parameters [68]. The correlation coefficient for the CNN is given by

$$\text{Correlation Coefficient} = (Con(x, \hat{y})/(\sigma x, \sigma\hat{y}) \tag{2}$$

Where x denotes real samples., ŷ denotes predicted samples, Cov(x, ŷ) represents the covariance between x and ŷ. ‘σ’ is the standard deviation. This is calculated for both x and ŷ. [69]. Another adaptive learning technique for addressing damaging learning rates is the root mean square propagation. RMSprop uses an exponentially weighted average to calculate the learning rate after each iteration, given by [70].

$$q_t = q_{t-1} + (1 - Y) \times p_t^2 \tag{3}$$

$$\Delta w_t = -\frac{qt}{\sqrt{qt} + \sqrt{\in}} \times p_t \tag{4}$$

$$w_t + 1 = w_t + \eta \times \Delta w_t \qquad ....(5)$$

where η represents initial learning rate; q_t denotes exponential average of gradients along w_j; p_t is gradient at time t along w_j; xt describes exponential average of squares of gradients along w_j; Y is the hyperparameter.

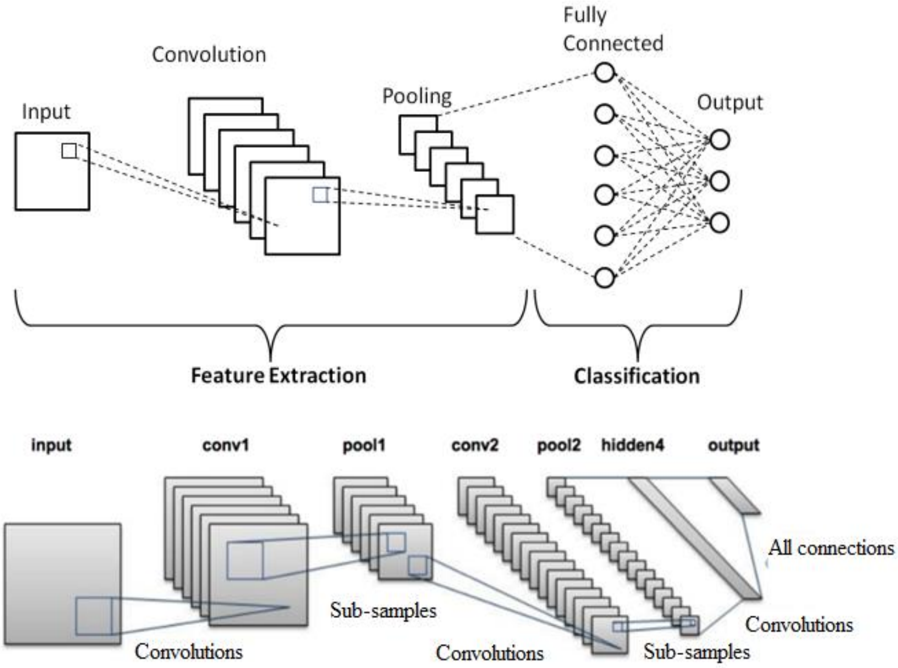

Fig 3. A detailed illustration of CNN

II. Materials and Methods

The process for conducting a systematic review of the documents is based on queries in the Scopus database integrated with PRISMA. The review methodology is based on earlier review techniques that were employed to build the state of the review on conventional neural networks in diverse applications [71–86]. The PRISMA found that the two most popular classical machine learning techniques are support vector machines and long-short term memories The following Figure illustrates the schematic representation of the methodology which is planned in three levels.

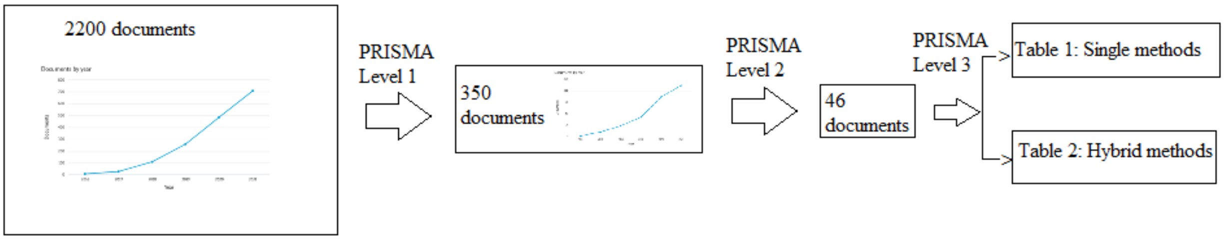

Fig 4. *The schematic representation of the methodology integrated with PRISMA*

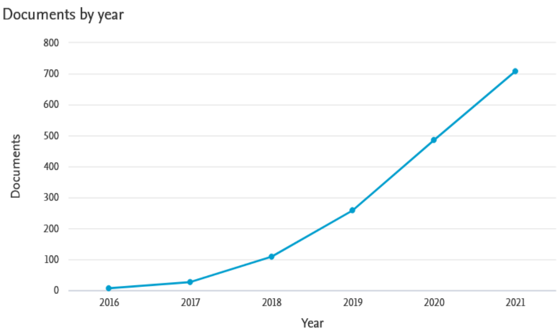

Fig 5. Illustration of the popularity of CNN in the smart grid within the past five years (2200 articles: source Scopus July 2022

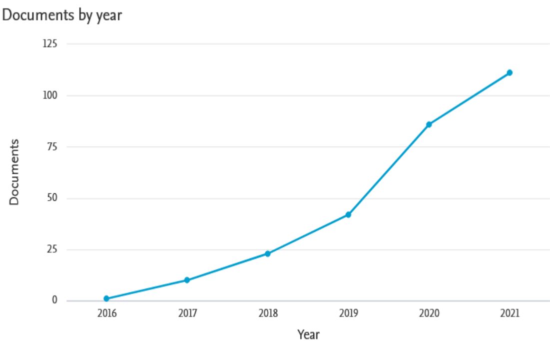

Fig 6 Identification of the fundamental and essential CNN using PRISMA guidelines (350 articles: source Scopus July 2022

III. RESULTS

The state-of-the-art review includes the single and hybrid CNN methods. The principal findings following the thorough survey and suggested model is that hybrid-CNN was found to be a very effective method. This can be used for abnormal flow detection in the software-defined network-based smart grid. The review demonstrates that using hybrid CNN improves accuracy. This is a significant advancement over using other deep learning techniques. Deep learning models are typically used with hybrid detection techniques to increase detection accuracy. The hybrid CNNs were employed to identify consumer electricity use fraud. New actors are being incorporated into the SG as it changes day by day. Consequently, new hybrid-CNN-based models and applications will be needed. The CNN-LSTM and CNN-GRU use different performance metrics like F-1 scores, precision, accuracy, and recall. The hybrid-CNN appears to have a bright future in smart grid applications. However, compared to shallow networks, these algorithms are more challenging to train. Their theoretical elements need to be investigated despite their widespread use and superior performance. Table 1 provides a summary of the single CNN approaches. Furthermore, the hybrid methods of CNN are listed and discussed in table 2.

TABLE I. Single CNN in smart grid

References	Year	Journal name	Application
[87]	2022	IEEE Transactions on Network Science and Engineering	Attack and defense to recognize power quality.
[88]	2021	Ad Hoc Networks	Internet-of-Things load identification.
[89]	2021	Computer Communications	Non-intrusive household load identification.
[90]	2020	IEEE Transactions on Industrial Informatics	Nonintrusive Load Monitoring
[91]	2020	PLoS ONE	Reduction and faulty data detection during the building of the smart grid.
[92]	2020	IEEE Internet of Things Journal	Detection of the fake data injection attack locally.
[93]	2020	International Transactions on Electrical Energy Systems	Enhancing security by identifying and categorizing non-technical losses.
[94]	2019	IEEE Internet of Things Journal	Protection of energy privacy and detection of energy theft
[95]	2019	Energies	Energy disaggregation
[96]	2019	WSEAS Transactions on Power Systems	Forecasting of sources and loads in smart grids
[97]	2018	IEEE Transactions on Industrial Informatics	Electricity-Theft detection
[98]	2018	Neurocomputing	Energy demand prediction

TABLE II. Hybrid CNN in smart grid

References	Year	Sources	Application	Name of the hybrid CNN
[99]	2022	Energies	False data injection and attack detection	Convolutional Neural Network, Auto-encoder, Long-short term memory
[100]	2022	Journal of Internet Services and Information Security	Cyber-security audit	Convolutional Neural Network, AlexNet, ,Long-short term memory
[101]	2022	Journal of Modern Power Systems and Clean Energy	Discreet load monitoring	Biology-inspired spiking neural network, spike-time dependent plasticity algorithm
[102]	2022	Journal of King Saud University - Computer and Information Sciences	Self-maintenance of smart grids	Convolutional Neural Network, Discrete Wavelet Transform
[103]	2022	IEEE Internet of Things Journal	Energy theft detection	Temporal convolutional network, FedDetect framework
[104]	2022	Energies	Manual operation evaluation and virtual reality training in Smart Grid	Vectorized spatio-temporal graph convolutional neural network,
[105]	2022	IEEE Access	Loss detection	Gray relational analysis, a quantizer based on D-H, and a classifier based on 1D CNN
[106]	2022	IEEE Access	Identification of non-technical losses	Bidirectional gated recurrent unit, Autoencoder
[107]	2022	Wireless Communications and Mobile Computing	Recognition of faulty electrical lines using the Internet of Things	Convolutional Neural Network, Relief-F
[108]	2022	IEEE Access	Data augmentation to detect non-technical losses	Bidirectional Wasserstein generative adversarial network, 2D- Convolution Neural Network
[109]	2022	IEEE Access	Electricity theft detection	AdaBoost and AlexNet, artificial bee colony optimized, Convolution Neural Network

[110]	2022	IEEE Transactions on Instrumentation and Measurement	Intelligent Aging Diagnosis of Conductor	AlexNet-based deep convolution network
[111]	2022	Applied Intelligence	Consumer behavior learning for real-time demand response implementation	Convolution Neural Network, Long-short term memory, Dynamic itemset counting, XG-boost
[112]	2021	Energies	Big data electricity theft detection	RUSBoost Manta Ray Foraging Optimization, Convolution Neural Network, and RUSBoost Bird Swarm Algorithm
[113]	2021	Sustainability (Switzerland)	Electric price and load forecasting	AdaBoost, support vector machine, convolutional neural network, Coronavirus herd immunity optimization
[114]	2021	Bulletin of Electrical Engineering and Informatics	Electricity-theft detection	Convolutional neural network, Sequential model
[115]	2021	Neurocomputing	Early warning classification for local-to-global perception	EWNet
[116]	2021	Journal of Parallel and Distributed Computing	Electricity theft detection	Convolution neural network, Long-short term memory, Adaptive synthesis
[117]	2021	Soft Computing	Damage power line detection	Convolution neural network, Support vector machine
[118]	2021	IEEE Access	Finding non-technical losses to secure smart grids	Time least square generative adversarial network, Gated recurrent unit, GoogleNet
[119]	2021	IEEE Transactions on Automation Science and Engineering	Interpretable of different machine learning algorithms in smart grid	Graph convolutional network, Time-series shapelet transform
[120]	2021	IEEE Access	Detection of Non-Technical Losses	Method of Synthetic Minority Oversampling Self-Attention Generative Adversarial Network, Edited Nearest Neighbor
[121]	2020	Security and Communication Networks	Abnormal Flow Detection	Adam, SGD, RMSprop, Adagrad

CONCLUSION

The convolutional neural network methodologies have been a fundamental deep learning solution to smart grid applications. It is essential to investigate and evaluate the progress of this method in the smart grid. Consequently, a comprehensive investigation with the aid of PRISMA had been conducted. The PRISMA standard queries including the convolutional neural networks and their abbreviation forms of ConvNet or convolutional neural reveal a significant increase in the popularity of this deep learning method in smart grid applications. This research identifies 2200 pieces of literature in the field. After considering the PRISMA guideline the most relevant and fundamental application had been reduced to 46 documents where the single and hybrid methods had been identified. The investigation showed that hybrid methods delivered a better performance with higher accuracy. It is expected that more hybrid methods will have emerged in the smart grid application. The literature demonstrates that a convolution neural network has been thought of as a workable alternative. In conclusion, this article will be interesting to aspiring researchers who may be keen to learn about the cutting-edge concepts required to understand convolution neural network use in smart grid technologies. In estimating individual household energy consumption with both predictable and regular usage behavior, the hybrid convolutional neural - long short-term memory-based deep learning architecture performs better than the other competing systems. Future work to improve classification accuracy will require additional research utilizing methods such as attention mechanisms, context-relation modeling, feature fusion of depth and infrared information, etc.

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