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REVIEW **Open Access**

Systematic literature review of the techniques for household electrical appliance anomaly detections and knowledge extractions

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Abstract

The demand for electricity at home has increased in recent times globally, this high demand for continuous, stable and affordable power can be attributed to the demand for comfortable lifestyle of consumers but the quality and efficiency of the appliances being used remain questionable. Malfunctioning appliances usually show a power signature statistically different from their normal behavior, which can lead to higher energy consumption or more serious damages. As a result, numerous studies in recent times have been conducted on the household electrical appliance anomaly behaviors to find the root-cause of these anomalies using machine learning techniques and algorithms. This study attempted to undertake a systematic and critical review of ninety-two (92) research works reported in academic journals over fifteen (15) years (2006–2021) in the area of household electrical appliance anomaly detections and knowledge extraction using machine learning. The various techniques used in these reports were clustered based on machine learning-based techniques, statistical techniques and physical based approach techniques and the parameters adopted, such as machine learning algorithms, feature extraction approaches, anomaly detection levels, computing platforms and application scenarios. This clustering was done based on the following criteria: the nature of a dataset and the number of data sources used, the data timeframe, the machine learning algorithms used, machine learning task, used accuracy and error metrics and software packages used for modeling. For the number of data source used, the results revealed that 81.2% of documents reviewed used single sources and Autoregressive integrated moving average (ARIMA) was the highest implemented regression model (60.9%), the probability model that was mostly implemented was the Bayesian network. Furthermore, the study revealed that, root-mean-square error (RMSE) accounted 35% was the most used error metric among household appliance abnormal behaviors, followed by mean absolute percentage error MAPE which accounted 32%. The study further revealed that 46% of appliance abnormal detections was based on weather parameters, and historical energy consumption. Finally, we recap the challenges and limitations for further research in electrical appliance anomaly detections locally and globally.

Keywords: Machine learning, Household appliance consumptions, Appliance anomalies, Appliance usage, Knowledge extractions, Artificial intelligence

Introduction

The cost of living is at its highest level in a decade particularly in Ghana, with household energy bills being the largest expense. In the year 2015–2017, the economy activities of Ghana became blank due to its energy crisis, this explains the pivotal role energy plays in the economic growth of any country. Every activity in this modern era depends on electricity particularly for any country that target development based on industrializations. Ghana envisages one-district-one factory which was crafted to industrialize the country but it could not be realized due to its insufficient electricity supply.

The reasons attributed to its shortfall of energy supply was outdated and unstandardized electrical appliance popularly called "second-hands", energy wastage by the consumer, unstable rainfall patterns, energy theft, and distribution and transmission losses which cause the government of Ghana selling its premier electricity distribution company- Electricity Company of Ghana (ECG).

Using energy efficient appliance will not only ensure that the hard-burden utility bills are soften but will also contribute to proper energy usage.

Undoubtedly, these reasons necessitate energy efficiency which has been gaining grounds across the globe.

In fact, energy efficiency can enhance the manner of buildings consume power in order to diminish detrimental effects on society, economy, and global environment [22]. Energy efficiency raises a serious concern as to how household appliances consume energy in building and their operational mode.

Appliance anomaly have a significant impact on energy efficiency, for this reason, end-users must use energy efficient and reliable electrical appliance that can mitigate the high end-user tariffs without sacrificing their living comforts and also timely detection of malfunctioning household appliance will go a long way to improve energy efficiency [4].

The contribution of knowledge from this research is stated as follows:

1. A detailed analysis on past primary studies on appliance anomalies detection techniques based on methods, detection level of the model, the computing resource the model is implemented on and the results obtained
2. A summary of the implemented algorithms, its classifications, identifying the strength and weakness of the algorithm, their detection accuracy, precision, recall values and the f-score values
3. Perform a quality assessment on past primary studies on appliance anomalies detection techniques
4. We present findings from the articles reviewed to serve as a guide in future research
5. Identify the challenges and the limitations of appliance anomalies detection schemes and the commercialization in the market industry
6. First reviewed article on household appliance anomalies detection techniques.

Methodology

The current study presents a systematic review of literature relating to the techniques deployed in appliance anomalies detections and knowledge extractions.

Data collection

A total of hundred and twenty (120) research works published in conferences, magazines and journals relating to the current studies were downloaded from the internet using keywords: machine learning, anomalies detection techniques, knowledge extraction, household electrical appliance and their computations while a total of ten (10) documents were sourced from other sources.

Study framework

According to David Moher, a systematic review should be built on protocol that defines the rationale, hypothesis and planned methods of the review but unfortunately, only few systematic reviews study reports on their study frameworks [23].

The "PRISMA" (Preferred Reporting Items for Systematic Review and Meta-Analysis) model was adopted in this current study; a well-structured detail systematic reviews that facilitate the understanding and evaluations of the methods being adopted by researchers. It outlines the total number of research identified, the inclusion and exclusion criteria, and the reasons for the inclusion and exclusion. The PRISMA model consists of five phases; phase 1: developing competency question, research scope, and "inclusion and exclusion" criteria. Phase 2: identification of potential areas with keywords in the literature. Phase 3: determination of articles relevance if the abstracts meet the inclusion and exclusion criteria. Phase 4: mapping of keywords for characterization of papers. Phase 5: the meta-analysis of studies in the review.

Our literature search online retrieved one hundred and twenty (120) and ten (10) from other sources, full text exclusion was performed and eighteen (18) duplicates were removed and additional twenty (20) articles were removed after further exclusion criteria were applied leaving the primary studies refined lists to be ninety- two (92). The digital libraries used include the following: springer open, IEEE, science-direct, research gate, and web of science. Figure 1 outlines the systematic processes followed.

Results and discussion

This section discusses the household appliance consumption pattern, the appliance classification and the anomaly detection techniques (methods) that have been implemented from the articles reviewed.

Overview of appliance anomaly detection techniques:

Household electrical appliance anomaly detections can be grouped into three (3) techniques, namely: machine learning-based techniques, statistical-based techniques and physical-based approach techniques as illustrated in Fig. 2

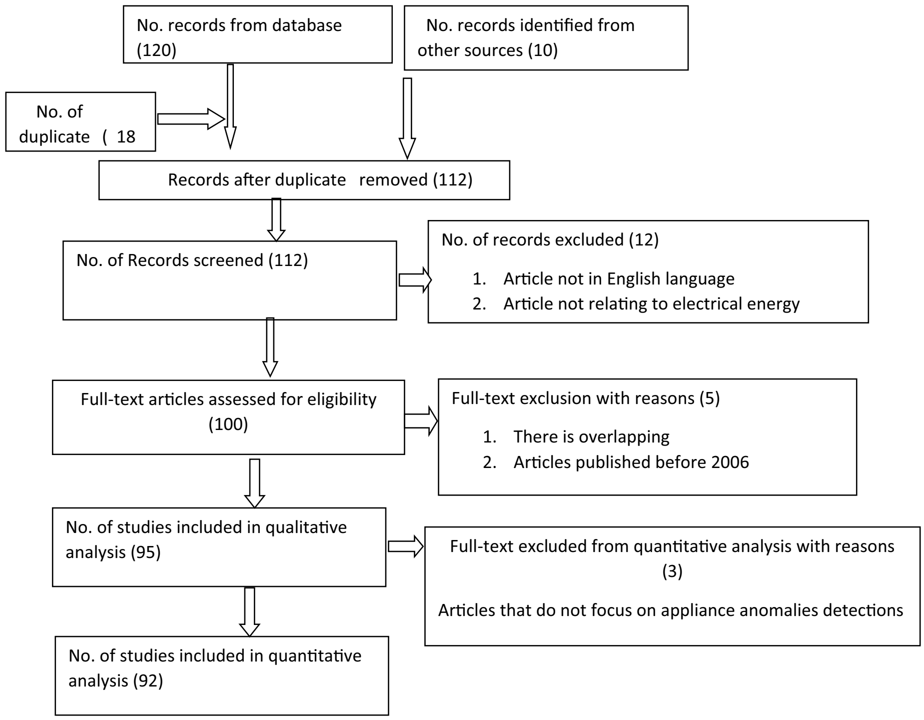

Fig. 1 Article selection procedure (PRISMA)

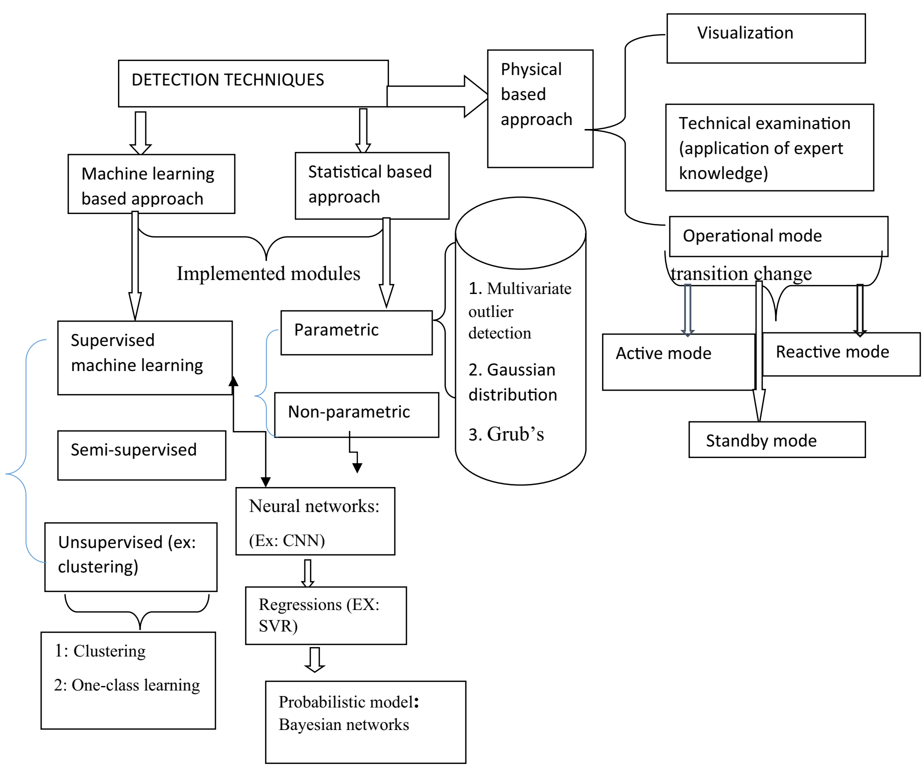

Fig. 2 Classification of detection techniques

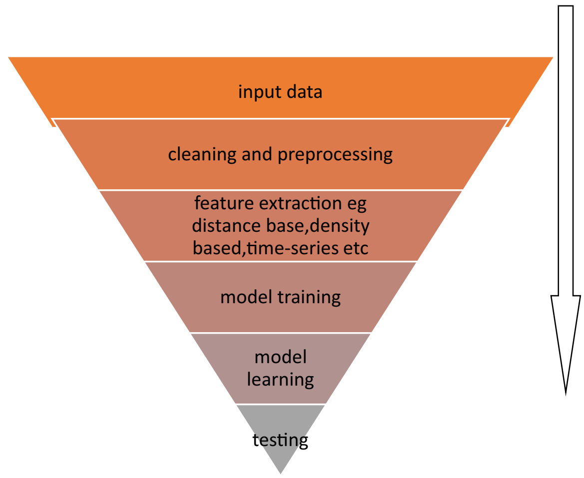

Fig. 3 Supervised learning adopted steps

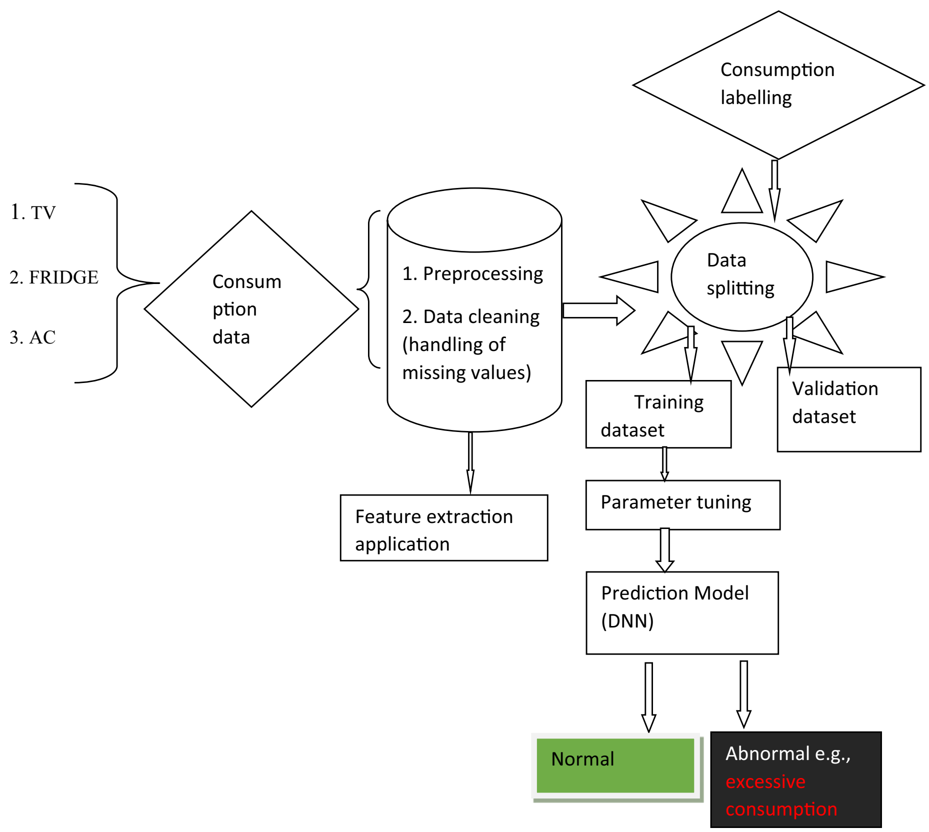

Fig. 4 Flowchart for supervised anomaly detections scheme

Supervised detection models

For a supervised detection model, the machine learning classifiers (binary or multi-class) are trained using annotated dataset where both appliance normal and abnormal consumptions are labeled. In academic research framework, the supervised models achieve higher accuracy in obtaining results but its implementation in the real world is limited as compared to unsupervised models as argued by [6, 7, 10] in their studies. Figure 4, indicates the flow chart of the supervised anomaly detection scheme.

Supervised anomaly detection processes

The consumption footprint of various appliances is collected, cleaned and pre-processed to remove and replace inconsistent records. As indicated in Fig. 3, important features are extracted using example time-series, graphed or density based. The power samples are labeled normal or abnormal for training data. The algorithm is chosen and the data are fitted into the model and validated. The fitted model is fine-tuned until satisfied for anomalous consumption detection for testing (Fig. 4).

Studies in [18] used KNN to detect appliance abnormal power consumptions, while studies in [11] have employed SVM to detect abnormalities in energy thefts. Further studies in [19] have used decision tree to learn energy consumption anomalies in appliance functions. Various regressions models have been introduced in studies [21] including support vector regressions (SVR), linear regressions, auto-regression, regression tress, and regression fitting to identify household appliance power consumptions anomalies.

Linear-based regression approach have been adopted in [30] studies to determine anomalous periods for individual homes to clear them and provide a precise energy consumptions pattern for the home.

Studies in [35, 36] have merged autoencoder and long-short term (LSTM) memory neural networks to detect abnormalities in unbalance power consumption dataset and achieved a satisfactory result.

However, convolutional neural networks (CNN) have proven to be more effective with superior performance in applications as compared to artificial neural networks in time series data. In [5 ,17], multi-scale convolutional recurrent encoder-decoder (MSCRED) has been used to detect abnormalities in analyzing multivariate time series observations. Whereas studies in [28] have employed generative adversarial networks (GAN) to deal with unbalances in anomaly detection datasets. They have demonstrated how GAN can be used to model high dimensional data of different categories including, images, time-series and cyber security.

Unsupervised detection models- one class learning:

It is built by grouping initial consumptions to normal or abnormal and then design a classification algorithm based on the grouping with the abnormality pattern either being poorly sampled or unclear. One-class learning presents a harder challenge to solve as compared to the conventional classifications [14, 27]. Studies in [3, 10] have employed kernel-based one-class neural networks to detect power consumption abnormalities with the aid of deep learning in representations of power signals.

Unsupervised detection models- dimensionality reduction algorithms

This approach can be used for classifications in another aspect of machine learning applications because of its low computational cost in removing irrelevant power consumption patterns example includes principal component analysis (PCA) in [24], linear discriminant analysis (LDA) in [36] and quadratic discriminant analysis (QDA) in [1, 8].

Semi-supervised Detection Techniques:

This is a hybrid method of machine learning where the normal power consumption of the household appliance is annotated which is widely adopted in many research frameworks [2]. In [16] deep auto-encoder is used to learn normal power consumptions in the absence of anomalous patterns. When adequate training consumptions observations are made from the normal patterns, the auto-encoder can generate low errors from the normal observations over the abnormal patterns. In [33] deep auto-encoder (DAE) is combined with k-nearest neighbors Graphs (KNNG) build a semi-supervised anomaly detection machine learning model.

Distributive analysis of data

A descriptive analysis of the current study outcome is presented in this section with its associated charts and tables.

Literature distribution

Table 1 shows the survey of works carried-out and categorized based on the techniques implemented: machine learning techniques, statistical techniques and combined analysis.

It is evident that machine learning techniques achieve detection accuracy of an average of 91.34%, statistical technique achieves detection accuracy of 93.68% and the combined method attain the highest scores of 97.85% this was analyzed using the "SPSS" (statistical package for the social sciences) tool.

Techniques performance evaluations

Authors evaluated their implemented techniques to assess its performance. Different error metrics have been implemented by researchers but this current study focused mainly on the most implemented metrics; these include RMSE "(Root Mean Square Error)", MAE "(Mean Absolute Error)", MAPE "(Mean Absolute Percentage Error)", and MSE "(Mean Square Error)." The root mean square error (RMSE) was the most implemented representing 35% while MAPE = 32%, MAE = 18% and MSE = 15%. The lower or smaller the value of the RMSE, MSE the better the detection accuracy since it is the measure of the error in the model [20].

Table 1 Categorization of implemented techniques

Categorization type	No of papers	Percentages (%)	Detection accuracy (Avg.) (%)
Machine learning	53	58	91.34
Statistical	21	23	93.68
Hybrids (combined	18	19	97.85
Total	92	100	100

Table 2 Algorithms grouping

Neural networks	No. of papers	Implementations (%)	Traditional classification	No. of papers	Implementations (%)
Convolutional neural networks (CNN)	23	25	Support vector machine (SVM)	37	40.2
Deep autoencoder (DAE)	16	17.4	k-nearest neighbors (KNN)	42	45.7
Deep belief network (DBN)	12	13.1	Logistic regression	13	14.1
Generative adversarial networks (GAN)	3	3.3			
Recurrent neural network (RNN)	16	17.4			
Multi-layer perceptron (MLP)	14	15			
Radial basis functional neural network (RBFNN)	8	8.7			
Total	92	99.9			100
Regression	**No. of papers**	**Implementations (%)**	**Probabilistic model**	**No. of papers**	**Implementations (%)**
Support vector regression (SVR)	27	29.3	Naïve bayes	38	41.3
Autoregressive integrated moving average (ARIMA)	56	60.9	Bayesian networks	54	58.7
Autoregression	9	9.8			
Hybrids	**No. of papers**	**Implementations (%)**	**Clustering**	**No. of papers**	**Implementations (%)**
Semi-Support vector machine (semi-SVM)	13	14.13	K-means	69	75
Deep autoencoder-k neural networks graph (DAE-KNNG)	8	8.70	C-means	11	11.96
			Mutual k-nearest neighbors (MNN)	3	3.26
			Entropy-based	9	9.78
One-class learning	**No. of papers**	**Level of implementations (%)**	**Dimensionality reduction**	**No. of papers**	**Level of implementations (%)**
One-class random forest (OCRF)	4	4.34	Principal component analysis (PCA)	17	18.48
One-class support vector machine (OCSVM)	3	3.26	Linear discriminant analysis (LDA)	11	11.96
One-class neural network (OCNN)	2	5.43	Quadratic discriminant analysis (QDA)	9	9.78
			Multiple discriminant analysis (MDA)	7	7.61

Table 2 (continued)

One-class learning	No. of papers	Level of implementations (%)	Dimensionality reduction	No. of papers	Level of implementations (%)
One-class convolutional neural network (OCCNN)	9	9.78			

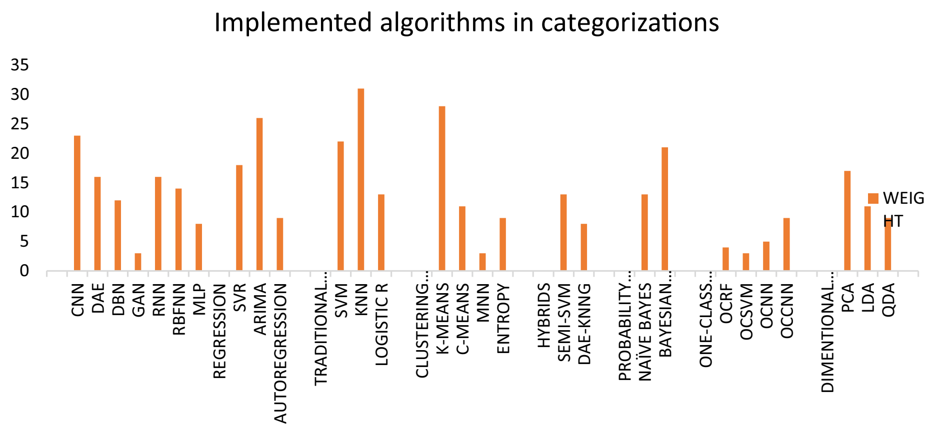

Fig. 5 Categorizations of implemented algorithms

Implemented algorithms distribution

From the 92 ([1–10], [11–20]) articles reviewed we quantified the algorithms implemented in the various articles as illustrated in Table 2, even though some researchers used multiple combinations of the algorithms. Identifying the algorithms and how it is implemented, will help in assessing its strength and weaknesses and the overall accuracy level of their model. The ANN model that was mostly used is the CNN representing 25% followed by the deep autoencoder (DAE) and recurrent neural networks (RNN) representing 17.4%. the traditional classification algorithm that was mostly implemented was the K- nearest neighbors (KNN) representing 45.7% and Autoregressive integrated moving average (ARIMA) was the highest implemented regression model scoring 60.9%, the probability model that was mostly implemented was the Bayesian network scoring 58.7% and semi-SVM was the most implemented hybrid method scoring 14.13% and the clustering algorithms that attained the most score was the k-means clustering representing 75%.

The dimensional reduction algorithm most implemented was the principal component analysis (PCA) representing 18.48% and one-class learning algorithm was the one-class convolutional neural network (OCCNN) attaining a higher score of 9.78% as illustrated in Table 2. The detail of the implemented algorithms with their categorization is visualized in Figs. 5 and 6 indicates implemented machine learning techniques.

Categorization of literature

A lot of factors were considered in categorizing the studied literature such as; appliance type used in the studies, the input parameters, the algorithm type, the algorithms

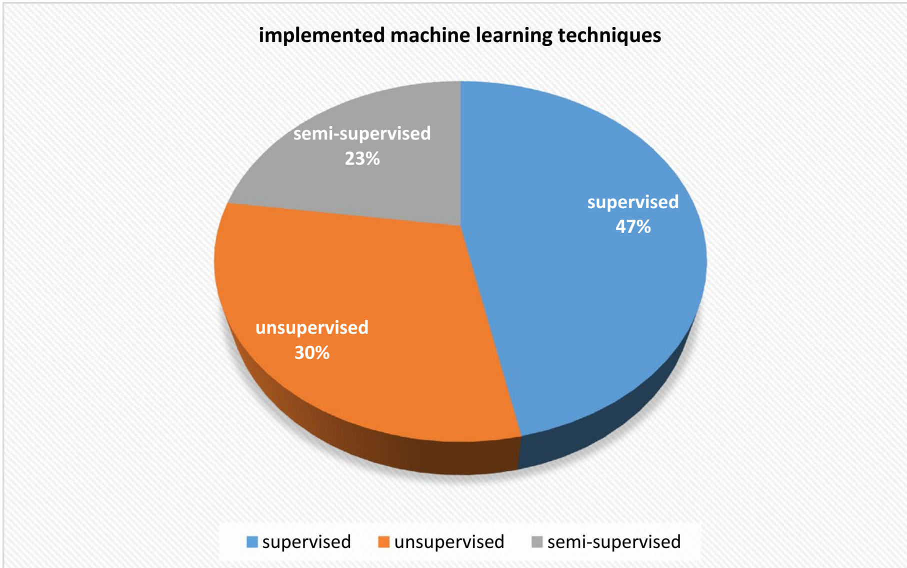

Fig. 6 Implemented machine learning techniques categorization

detection level (where the algorithms is implemented), the computing platform the algorithm is implemented and the final output of the model [9, 15, 32, 26, 31, 34]. This is simplified in Table 3 as illustrated.

In category 1 (CAT 1), 38 research articles reviewed representing 41. 30% used a supervised machine learning technique in their implementations achieving an average detection of appliance anomalies of 87.62% as a cumulative measure with majority using the edge computing resource at appliance or aggregated detection level. The household appliance considered in this category includes Television, Fridges, Freezers, Dishwashers, Air-conditioners and Microwave and the input parameters were; Operational mode, Time and usage frequency of the appliance. In CAT 2, 42 reviewed articles representing 45.65% used supervised model achieving average accuracy rate of detection 88.23% using the edge computing resource platform at appliance or aggregated level of detection. Their model was based on historical consumption and weather parameters as their input data and the household appliance studied includes the following: Fridge, Air-conditioners, Lighting, Microwave, Heaters, Irons, Blenders, Laptops, Speakers and Fans.

In CAT 3, nine (9) reviewed articles representing 9.78% of the 92 articles used supervised machine learning achieving an average detection rate of 78.42% implemented at an aggregated level. Out of the 9 articles, 3 used the edge computing platforms in their implementations, 2 researchers used the hybrid computing resource and 4 articles reviewed did not specified their computing resource the model was implemented on. The 9 articles used parameters such as Operational time, Operational mode, Appliance model, Occupancy and Power ratings and their studied household appliances include the following: Dishwashers, Air-conditioners and freezers.

In CAT4, 3 articles reviewed used a supervised machine learning model, one article implemented their model on an edge resource platform at appliance level, whiles one

Table 3 Article grouping on appliance, parameters, and computing platforms

Appliance	Parameters	Detection level	No. of papers	Stated algorithms type				Computing platform				Results
CAT 1				**Sup**	**Semi**	**Unsup**	**Stat**	**Edge**	**Fog**	**Hybrids**	**Un specified**	**% (Avg.)**
Television Fridges Freezers Dishwashers Air-conditioners Microwave	Operational mode Time usage	Appliance level detection, Aggregated level	38	11	9	7	5	21	11	2	6	87.62
CAT2												
Fridge Air-conditioners Lighting Microwave Heaters Irons Blenders Laptops Speakers Fans	Weather Historical -consumptions	Aggregated level and Appliance level	42	19	4	7	12	29	4	–	9	88.23
CAT 3												
Dishwashers Air-conditioners Freezers	Operational time, Operational mode Appliance model, Occupancy Power ratings	Aggregated level	9	7	–	–	2	3	–	2	4	78.42
CAT 4												
Fridges Air-conditioners Laptops Blenders Speakers Fans Oven television	Input voltages, Input current, Power rating	Spatio-temporal, Appliance level and Aggregated level	3	2	–	–	1	1	1	–	1	79.57

implemented their model on a hybrid computing platform at an aggregated level and the third article did not specified their computing resource their model was implemented on but the detection occurred at spatio- temporal level, the 3 articles achieved an average detection rate of 79.57% using input parameters such as Input voltages, Input current, and Power rating and their studied appliance includes the following: Fridges, Air-conditioners, Laptops, Blenders, Speakers, Fans, Oven, and television.

The most used machine learning detection technique is the supervised model, this is due to the type of input parameters used. The edge and the aggregated computing resources were the most used computing platforms.

The most used feature extraction tool is the distanced-based, follow by a time-series analysis. This can be attributed to the type of input data and in this case, appliance functions dataset is time and distance attributes. The nature of data extraction tool used by the 92 reviewed articles is cumulatively analyzed as illustrated in Fig. 7.

Top ten articles

From the 92 articles reviewed, "(Wu et Pend, 2017) model" achieves the highest scores in accuracy, precision, f-score and recall values. The dataset was the largest (17,200) and the model was implemented at appliance level but they however used a private data source which is difficult to verify. The details of the top ten (Wu et al.. 2019, Chen et al.. 2021, Wang et al.. 2017 Rosni et al.. 2010, Zuffrey et al.. 2011, Albert et al.. 2012, Michael et al.. 2012, Wan et al.. 2018, Hassan et al.. 2015, Yang et al.. 2019) best performing models based on their evaluation metrics are illustrated in Table 4. The algorithm strength of the implemented models can be very difficult to be compared with other model because of the type and source of the dataset and the detection level of the models. Private data source has difficulties in assessing them for verifications and some of the public datasets are constantly being updated or modified from time to time.

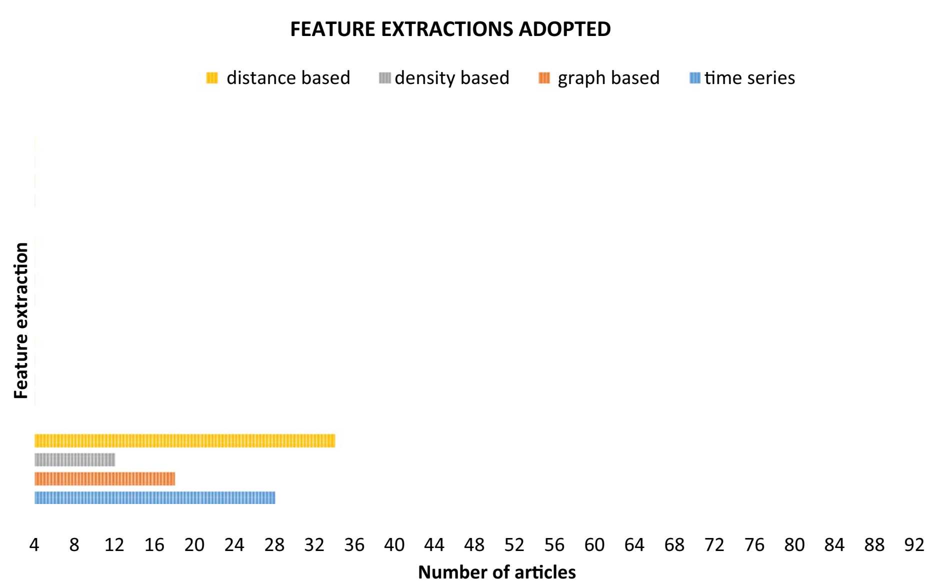

Fig. 7 Feature extraction analysis

Table 4 Top studies analysis

Primary study	Year	Data size	Data source	Detection level	Performance (%)	Remarks
Wu et al.	2019	17,200	Privates	Appliance level	Accuracy: 99.31 Precision: 99.8 f-score:98.97 Recall: 97.21	Positive: the author used four performances metrics to evaluate their model they achieve the highest score in their performance index. This can attributed to their large data size Negative: Their results cannot be verified because they used a private data source. Private data source is a restricted access
Chen et al.	2021	15,132	Private	Aggregated level	Accuracy: 98.72 f-score: 98.57 MAPE: 3.87 RMSE:5.32	The author achieves a significant accuracy a lower or smaller MAPE and RMSE values is an indication of a good performance model
Wang et al.	2017	11,200	Privates	Aggregated level	Accuracy: 98.51 Precision:98.23 F-score: 97.85 Detection rate:97.60 Recall: 96.87	Higher scores in accuracy, precision and f-scores value and detection rate
Rosni et al.	2010	10,300	Public	Appliance level	Accuracy: 97.65 f-score: 96.23 RMSE: 4.56 MAPE: 6.71	Appliance anomalous behaviors were detected this was measured with a higher accuracy and f-score with a lower RMSE and MAPE
Zuffrey et al.	2011	10,230	Private	Aggregated level	Detection rates:96.79 Recall value: 96.35 Precision: 97.23 f-scores: 95.98	Higher scores in detection rate, recall values with higher precision and f-score values
Albert et al.	2012	9700	Public	Aggregated level	F-score:95.67 Detection rate:96.67 MAPE: 8.67 RMSE: 5.55	The authors achieves a smaller MAPE and RMSE values with a higher detection rate
Michael et al.	2012	9450	Private	Aggregated level	Accuracy rates: 97.57 Precision: 96.87 f-score: 95.65 Recall: 95.97	This research attains a higher accuracy rate and precision, a higher f-score and recall value
Wan et al.	2018	220	Private	Aggregated level	Accuracy: 97.23 Detection rate:95.65 f-score: 95.34	The authors achieve a higher value of accuracy and detection rate of their model but with a lower data size

Table 4 (continued)

Primary study	Year	Data size	Data source	Detection level	Performance (%)	Remarks
Hassan et al.	2015	385	Public	Aggregated level	Accuracy: 96.87 f-score:91.09 RMSE: 9.53 MAPE:11.01	A lower score in RMSE and MAPE which is an indication of good performance model
Yang et al.	2019	289	Public	Aggregated level	Accuracy:89.78 Detection rate:85.12 Precision:94.58 f-score:88.07 Recall:91.43	The authors achieve a good performance model based on their performance metrics. However, the data size is small and that contribute to its good performance

Primary study	Techniques used	Technique advantage	Major limitation	Results obtained
Wu et al.	Mutual K-Nearest Neighbor (MNN) And K-Means clustering	Annotated data are not required	ONLY appliance excessive consumptions are detected	Appliance anomalous behaviors are detected in their consumption patterns
Chen et al.	Convolutional neural network (CNN)	This techniques detects abnormal power usage in a higher accuracy	The techniques has a high computational cost It lacks annotated data	The techniques was able to detect high consumption by the appliance
Wang et al.	CNN AND and Random Forest (RF)	The techniques achieves high anomaly detection performance	The technique has high computational cost	It was able to analyze energy consumption data
Gonzalez et al.	ANNs and ARIMA	It Predicts appliance energy usage And detects anomalies with high accuracy	The techniques have high training cost	Appliance excessive consumptions are detected
Albert et al.	SVM, Deep neural network (DNN) Local outlier factor (LOF), KNN	The technique was able to detect different appliance anomalies	It lacks annotated data	Anomalies was detected with high performance
Michael et al.	Gaussian distribution	The techniques has a low training cost	There is lack of annotated data	The techniques was able to detect excessive consumption of the appliance
Wan et al.	Gradient Boosting Machine (GBM)	The technique was able to Predict power usage and Detect appliance anomalies	The techniques has a low interpretability	The anomalies that are detected are suspicious ones and may be the actual if Cross validated
Zuffrey et al.	Deep autoencoder (DAE)	The technique is able to predict Appliance energy usage and detect Anomalies	The techniques has a high computational cost	The techniques was able to detect anomalies with high accuracy
Yang et al.	SEMI-SVM	The technique was able to predict Appliance energy usage and detect Anomalies	The technique has a weak interpretability	The technique was able to detect anomalies but based suspicion level
Hassan et al.	Convolutional neural network (CNN)	The technique was able to detect appliance anomalies with privacy preservation	The technique has a weak interpretability	Appliance anomalies was detected with high accuracy

Table 5 Studies origin

Origin	Number of papers	Representation (%)
Africa	7	7.61
Asia	37	40.22
USA	18	19.57
Europe	5	5.43
Austria	11	11.96
Unspecified	14	15.21
Total	92	

Table 6 Quality assessment

Attributes	Yes (No.)	Yes (%)	No (No)	No (%)	Partly (No)	Partly (%)
Clear objective of studies	92	100	00	00	00	00
Sufficiency of data size	79	85.87	4	4.35	7	7.61
Clear data collection procedures	85	92.40	2	2.17	5	5.43
Provision of experiment details	89	96.74	00	00	3	
Provision of threat to validity	00	00	91	98.91	1	1.10
Provision of study limitations	6	6.52	85	92.40	1	1.10
Provision of clear learning defined techniques	87	94.57	00	0	5	5.34
Studies provision of clearly defined performance parameters	83	90.22	3	3.26	6	6.52
Provision of clearly stated results	88	95.65	00	00	4	4.35
Provision of comparisons of techniques	78	84.78	7	7.61	7	7.61
Addition of value to existing knowledge	82	89.13	00	00	10	0.87
Studies provision of tools or online source code	4	4.35	86	93.48	2	2.17

Article studies origins

Table 5 shows the origin of articles, the origin of articles was critically asssesed to help examine the impact of weather parameters on appliance malfuctioning since each continent experiences different weather conditions, also to asses the impact of size of occupancy on appliance functioning and also the effect of usage patterns (lifestlye impact) on the appliance functioning. Africa and Asia usually have a larger family size [12] as compared to the other continent for these reasons, it is important to examine the origin of articles and from Table 5.

Articles quality assessment report

We perform a quality assessment on each study to determine the validity of the research carried-out. Selected attributes and clear procedures were used in the quality assessment as illustrated in Table 6.

All the 92 reviewed articles have a clear studies objective and 79% of the total actually used a sufficient data size. A clear data collection procedure was followed in their data collections and 89% provided a clear stated detail about their experiment but a large number of 85% fails to provide a limitation in their research and the challenges they encountered in the processes of building and implementing their models.

About 99% of the research articles fail to perform validity test to assess the threats their model validity but however, 83% of the studies provided a clearly defined performance parameter. A significant number of 88% achieved and stated a clear finding in their research. This knowledge is useful in future research.

Market deployment and difficulties of anomaly detection techniques

We try to examine and assess how the appliance anomaly detection techniques could be deployed in the current global markets and perhaps assessed the difficulties associated with the implementations. The electronics, electrical and in general the digital market is growing at a robust rate and anomaly detections will play an integral part in its growth [13, 29]. Active utilities and energy companies' providers are not left out in providing appliance anomaly detections and energy monitoring solutions. Previous methods of detecting appliance malfunctioning were based on data provided by electricity consumption meters. However, the consumptions meters lack or do not provide vital information for details analysis of appliance malfunctioning, Table 7 summarizes the techniques that have been developed and implemented at various level in the market. Their models detect the appliance anomalies in real time or near real time, the frequency of detections, the solutions and the environment the detects can be implemented.

Inspite of their solutions, the implementations come with some difficulties as summarized:

1. High implementation cost.
2. Anomalies detections techniques scalability, speed and privacy preservations
3. Research consensus on implemented algorithms
4. Industrial commercialization difficulties due to the requirement high computing resource example cloud computing resources of the techniques

Table 7 Anomaly detection solution for households

Product	Manufacturer	Implementation type	Solution	Implementation environment
InBetween	Ecoisme	Model is connected to local wi-fi	It provides appliance consumption statistics through mobile apps	Household
Informetis	Informetis	The model uses IoT and data mining technologies	It provides near real time energy monitoring	Household
Neurio	Neurio	Appliance consuming more than 400w	Real time appliance anomaly detection and notifications	Household
WiBee Home	Wibeee	It combines appliance recommended energy savings and cloud computing	Appliance real time consumptions visualizations and anomaly detections	Household
HOMEpulse	HOMEpulse	It provides appliance real time energy disaggregation and anomaly detection	It provides solution with 1–10 s of sampling rate	Household
HiveSTARTER Pack	AlertME	It controls appliance using a mobile app	It monitors electricity at the household level	Household

Appliance anomaly detection challenges and limitations

There are challenges and limitations in implementing household appliance anomalies detection techniques. From the articles reviewed, we identified and summarizes those challenges and limitations as:

1. Dataset class imbalance: the class imbalance of the dataset affects the overall performance of the algorithms and to solve this challenge, data pre-processing is required example includes but not limited to (1) resampling technique to bridge the minority and majority classes (2) generating real time or near real-time appliance energy consumption data.
2. Absence of label dataset: what is normal or abnormal in appliance consumption in the dataset is a serious challenge in validating appliance abnormality detection schemes and creating a labeled dataset is a challenge and its availability is difficulty.
3. Appliance anomalies detection scheme with its implementations at the appliance level is still receiving less attentions.

Conclusion

Household appliances malfunctioning has a serious financial burden on the end-users and great threat to energy savings in general and it is these reasons that appliance anomalies detection is of great importance. A lot of anomalies detection techniques have been proposed by researchers achieving significant results but however their implementation in the market remains a serious challenge.

Most of the researchers mainly focus on anomalies detection at the aggregated level with little attention at the appliance level.

More research efforts are needed in overcoming the stated challenges and limitations in building a power anomalies detection model that can preserve end-user privacy since privacy is a primary concern of the end-user. Another concern in future research is a detection model that is scalable with high detection speed with accuracy and low implementation cost which can be commercialized for easy accessibility by all user.

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Author contributions
A detailed analysis on past primary studies on appliance anomalies detection techniques based on methods, detection level of the model, the computing resource the model is implemented on and the results obtained (performed by SAAR), Questionnaire development, data gathering and survey were carried-out by SAAR, Data preprocessing and analysis were performed by AFA, Quantitative and qualitative analyses were performed by AFA, Manuscript development was performed by SAAR, AFA revise the manuscript writing, Results analysis and interpretation was supervised by AFA, A summary of the implemented algorithms, its classifications, identifying the strength and weakness of the algorithm, their detection accuracy, precision, recall values and the f-score values (performed by SAAR), Perform a quality assessment on past primary studies on appliance anomalies detection techniques (evaluated by AFA), Identify the challenges and the limitations of appliance anomalies detection schemes, and the commercialization in the market industry (performed by SAAR), All authors read and accepted the final manuscripts and choice of journal.

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