Available online at www.dergipark.org.tr/en

INTERNATIONAL ADVANCED RESEARCHES
and
ENGINEERING JOURNAL

Journal homepage: www.dergipark.org.tr/en/pub/iarej

e-ISSN: 2618-575X

International Open Access

Volume 05
Issue 02

August, 2021

Research Article

A comparative study on appliance recognition with power parameters by using machine learning algorithms

Yılmaz Güven [a,*]

[a]*Vocational School of Technical Science, Kırklareli University, Kırklareli 39100, Turkey*

ARTICLE INFO

Article history:
Received 03 February 2021
Revised 24 May 2021
Accepted 18 June 2021

Keywords:
Appliance recognition
Data pre-processing
Feature extraction
Grey relational analysis
Machine learning

ABSTRACT

Recently, machine Learning algorithms are widely used in many fields. Especially, they are really good to create prediction models for problems which are not easy to solve with conventional programming techniques. Although, there are many different kinds of machine learning algorithms, results of applications are varying depend on type of data and correlation of information. In this study, different machine learning algorithms have been used for appliance recognition. The measurement data of Appliance Consumption Signatures database and some derivative values have been used for training and testing. Additionally, a data pre-processing technique and its effects on results have been presented. Filtering corrupted data and removing uncertain measurement value has improved the quality of machine learning. Combination of machine learning algorithms is best way to work with uncertain values. Different feature extraction methods and data pre-processing techniques are crucial in machine learning. Therefore, this study aims to develop a high accurate appliance recognition technique by combining grey relational analysis and an ensemble classification method. The results of this new method have been presented comparatively to show the improvement for itself and previous studies that uses the same database.

1. Introduction

Energy saving techniques are current discussions because of increased energy consumption rates. Nearly, half of all energy consumption is related to buildings and houses all over the world. That is why, attentions to smart homes and smart energy distribution system are on high demand. The main purpose of a smart system is being aware of all information around it. This way it can calculate, predict and make planning for better working conditions.

In this study, we have focused on appliance recognition techniques for buildings and houses. It is crucial to know which appliance is working and how often it is on for prediction of energy consumption. On the other hand, this information might be useful for other smart system such as security, telemetry and smart grids. There are many recognition and prediction methods in data science. Engineering methods, Statistical methods, neural networks, support vector machines and grey models are commonly used [1]. Home energy management system with load monitoring and power scheduling has already facilitated [2]. Prototype of low-cost power smart meter has been developed for photovoltaic prosumers [3].

Furthermore, many datasets have been established for appliance recognition and identification. The most recent one is a voltage and current measurement dataset for plug loads [4]. This data set contains 17 different appliances from 330 different makes and models. The another one is

ACS (Appliance Consumption Signatures) database [5]. We have preferred to use this database for our study because of its low sampling frequency. This database contains 15 different appliances from 225 brands. It also has two separate measurement sessions for training and testing. Some other researchers have also focused on real-time recognition and profiling by using a single electricity sensor [6]. All these works show us that future of electric

* Corresponding author. Tel.: +90 288 214 1845; Fax: +90 288 214 1495.
E-mail addresses: yilmaz.guven@klu.edu.tr *(Y. Güven)*
ORCID: 0000-0002-8205-2490 *(Y. Güven)*
DOI: 10.35860/iarej.873644

energy delivery and management systems cannot be apart from information system and internet technologies [7].

Previous studies show that it is hard to detect some appliance while some are easy. Different data preparation techniques have been used for better accuracy. For example, moving average technique has been used with machine learning algorithms [8]. Result of this work was promising but dataset was limited. Some other researchers who have been using the extended database for developing automatic household appliances identification [9] have achieved relatively better results. On the other hand, non-intrusive methods show that more than one identification techniques improve the accuracy of the system [10].

Future of intelligent power system is depending on machine learning algorithms. Identifying loads and forecasting electricity consumption is crucial. Ensemble machine learning based artificial neural networks can ben used for load forecasting [11]. Non-intrusive appliance recognition techniques can be applied by using machine learning for better and low-cost intelligent measurement device [12]. It is really important to identify power consumption of different appliance from a single metering point in smart buildings [13].

Building automation and management systems require real-time, end to end solitons for appliance recognition as internet of things device [14]. Smart outlets are easiest way to measure and identify each individual appliance with simple machine learning techniques [15].

All these studies show that data preparation techniques and classification methods must be choose wisely. In this study, some popular machine learning algorithms have been compared by using latest ACS dataset for appliance recognition. The advantages of different data pre-processing and feature extraction techniques have been cited.

2. Material and Method

2.1 The Database

The ACS database contains electrical consumption signatures of 15 different appliance categories with 225 different brands. The measurements (Table 1) of real power, reactive power, frequency, phase angle, RMS current and RMS voltage were recorded at low sampling frequency as 0,1 Hz [16]. Low sampling rate is good for both energy saving and reducing the data size.

Table 1. The measurement detail of dataset

Value	Symbol	Unit
Frequency	F	Hz
Phase Angle	φ	º
Real Power	P	W
Reactive Power	Q	VAR
RMS Current	IRMS	A
RMS Voltage	VRMS	V

The database has two distinct session for different measurements. The first one is for using as training data and the second one is for testing purpose. This way, we can test the system with new unknown data. The database contains hours of measurement data which provide us more than eighty thousand samples of 15 different appliances.

2.2 Pre-processing

Real world data must be pre-processed for preparation before analysis. There are many different types of data pre-processing techniques. The main purposes of these techniques are removing errors, noises and inconsistent data as much as normalize and improve the quality of the data [17].

All measurements contain samples in time series so they need to be expressed with dynamic coefficients. The coefficient can be calculated by using different methods such as moving average, velocity and acceleration or standard deviation. On the other hand, normalization of these data is another step of data preparation. This study will demonstrate a combined data preparation technique which does both calculating dynamic coefficients and normalize the data at the same time.

Grey Relational Analysis (GRA) is a new approach in grey system theory. It is good for calculating the relation between multiple factors and variable. Since our data has different range with different units, it is good to use GRA for pre-processing. You can choose whether higher-better as in Equation (1) or lower-better as in Equation (2) approach in GRA. It means that your data will reference 0 or 1 depends on your approach [18].

$$X_i(k) = \frac{X_i - minX_i}{maxX_i - minX_i} \tag{1}$$

$$X_i(k) = \frac{maxX_i - X_i}{maxX_i - minX_i} \tag{2}$$

Where i represent the original sequence index number and k represent after pre-processing, max and min are the maximum and minimum value of the data sequence.

Then the deviation sequences as in Equation (3) and grey relational coefficient can be calculated by using Equation (4).

$$\Delta i(k) = |X_i(k) - X_0(k) \tag{3}$$

$$C_i(k) = \frac{\Delta min + q\Delta max}{\Delta_i(k) + q\Delta max} \tag{4}$$

Where X0 is reference sequence, Δmin and Δmax minimum and maximum values of Δi and q is adjustment coefficient which is between 0 and 1 (normally 0.5).

Finally, grey relational grade (GRG) for each sample can be calculate as in Equation (5).

$$\mathrm{Y_i(k)} = \frac{1}{\mathrm{n}} \sum_{\mathrm{k=1}}^{\mathrm{n}} \mathrm{C_i(k)} \tag{5}$$

Where Yi represents GRG, which is the correlation level of normalised inputs, k=1...n; n is the number of the parameters, i=1…m; m is the number of the data items in the sequence.

2.3 Machine Learning

Machine learning (ML) can be describe as building a model from previous experience to predict outcomes of future problems. Most popular applications of ML are used for classification, data preparation, supervised learning, generalization, support vector machines, decision trees, nearest neighbour and clustering. For better accuracy and speed more than one technique can be used combined for ensemble learning such as boosting, bagging, random subspace and predictors ensemble [19].

A learning algorithm can be supervised, unsupervised or reinforcement. Supervised means input and target vectors are together in the training set while unsupervised learning doesn't contain target vector in the training set. This is also known as labelling. The reinforcement learning doesn't need labels as it takes action in order to maximize notion of cumulative reward [20].

Decision trees are fast and use less memory but they have low predictive accuracy. Discriminant analysis methods are fast and accurate but they are not flexible. Support Vector Machines are hard to interpret and use large amount of memory. Nearest neighbour classifiers generally have good results in low size data with high memory usage. For these reasons, ensemble classifiers are generally used to combine more than one learning technique to build a high-quality model (Figure 1).

Although, there are many ensemble methods by manipulating error function, labels, feature space, training or test parameters; three general approaches emerge [21]. The first approach is Majority voting as in Equation (6) which is the simplest one because it neither requires previous data nor complex computation. However, it can make poorly decisions because it votes all classifier equally so a weighted voting as in Equation (7) can improve the result by reducing effect of poor classifiers. Furthermore, a Bayesian combination as in Equation (8) makes each classifiers' error can affect the result with different weights by using previous knowledge [22].

$$C_e = arg\ max\{\sum_{n=1}^{k} S_i C_n\} \tag{6}$$

$$C_e = arg\ max\{\sum_{n=1}^{k} W_n S_i C_n\} \tag{7}$$

$$C_e = arg\ max\{\mu \prod_{n=1}^{k} P(C_i|C_n)\} \tag{8}$$

Where Ce ensemble output, Cn is the class, Si is the classifier (1≤ i ≤m), Wn is the weight of nth classifier as follows in Equation (9).

$$\mathrm{W_n} = \frac{\mathbf{1-E_n}}{\sum_{\mathbf{k}}(\mathbf{1-E_k})} \tag{9}$$

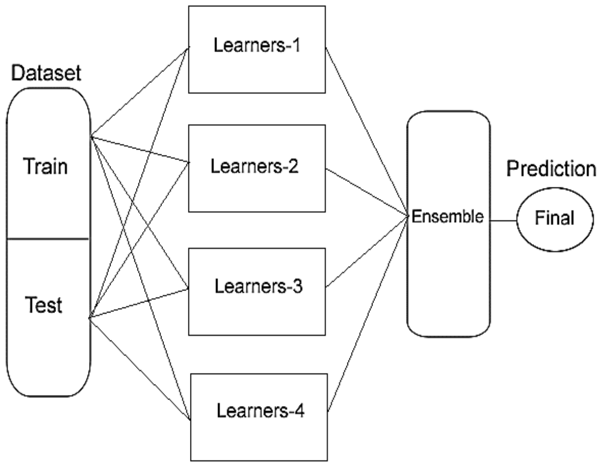

Figure 1. Ensemble Techniques Diagram

Where En is the error of nth classifier and Ek is the error of combined classifiers.

3. Result and Discussion

The database contains 15 different appliance types with 15 different brands. Active and reactive power distribution of the appliances is shown in Figure 2. For better feature extraction, derivative values such as apparent power as in Equation (10), power factor as in Equation (11), active as in Equation (12) and reactive power as in Equation (13) have been created by using database measurement data.

$$S = \sqrt{P^2 + Q^2} \tag{10}$$

$$cos\varphi = \frac{P}{S}\ ,\ sin\varphi = \frac{Q}{S} \tag{11}$$

$$P = V_{RMS}.I_{RMS}.cos\varphi \tag{12}$$

$$Q = V_{RMS}.I_{RMS}.sin\varphi \tag{13}$$

Where S is apparent power, P is active power, Q is reactive power, φ is power factor, Vrms and Irms are root mean square value of voltage and current.

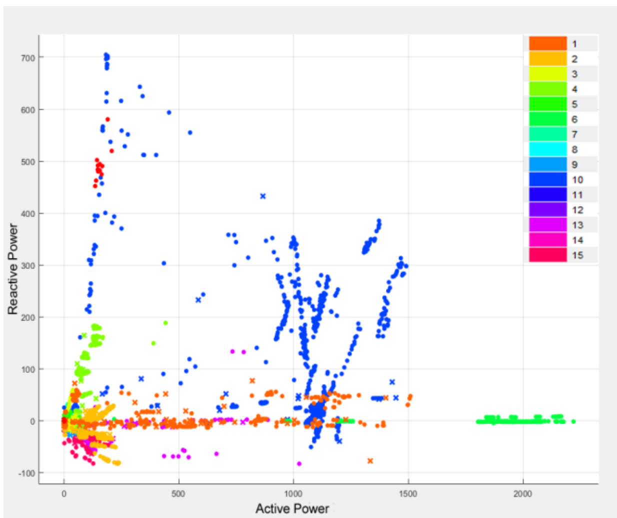

Figure 2. Distribution of classes

Table 2. Raw data and 6 features

Classifier	Type	Train	Test	Drop
Decision Tree	Fine	63.9%	57.7%	6.20%
Discriminant	Linear	26.6%	26.15%	0.45%
Naïve Bayes	Kernel	55%	53.06%	1.94%
Support Vector Machine	Fine Gaussian	76.7%	64.53%	12.17%
k-Nearest Neighbor	Fine	77.6%	62.51%	15.09%
Ensemble Method	Bagged Trees	81.4%	72.9%	8.50%

Table 3. Raw data and 12 features

Classifier	Type	Train	Test	Drop
Decision Tree	Fine	67.9%	62.95%	4.95%
Discriminant	Linear	39%	38.45%	0.55%
Naïve Bayes	Kernel	56.5%	54.09%	2.41%
Support Vector Machine	Fine Gaussian	79%	69.38%	9.62%
k-Nearest Neighbor	Fine	78.9%	64.22%	14.68%
Ensemble Method	Bagged Trees	80%	73.05%	6.95%

Table 4. GRA data and 6 features

Classifier	Type	Train	Test	Drop
Decision Tree	Fine	85%	81.65%	3.35%
Discriminant	Linear	54%	51.2%	2.80%
Naïve Bayes	Kernel	40.7%	35.6%	5.10%
Support Vector Machine	Fine Gaussian	91.8%	80.16%	11.64%
k-Nearest Neighbor	Fine	98%	80.93%	17.07%
Ensemble Method	Bagged Trees	98.8%	88.28%	10.52%

Table 5. GRA data and 12 features

Classifier	Type	Train	Test	Drop
Decision Tree	Fine	85.3%	81.88%	3.42%
Discriminant	Linear	62.4%	52.23%	10.17%
Naïve Bayes	Kernel	41.4%	36.98%	4.46%
Support Vector Machine	Fine Gaussian	97.3%	85.08%	12.22%
k-Nearest Neighbor	Fine	98.7%	84.08%	14.62%
Ensemble Method	Bagged Trees	99.2%	93.5%	5.70%

As it can be seen from Figure 2, distribution of classes is too complex for one classification techniques. For this reason, we have used an ensemble machine learning technique. This way, results of more than one classifier could be combine for better classification as it was stated before. Furthermore, derivative features have been extracted from measured values. This improves the accordance between training and test accuracy. However, it can be seen that derivative features do not help to improve the total accuracy of the classifier. This can be seen on Table 2 and Table 3.

On the other hand, data pre-processing technique which is grey relational analysis here, has helped the machine learning algorithm to get better accuracy rating. This is because the invalid measurement data have been removed by comparing measured and derivative data. Grey Relational Analysis is a normalization technique which also provide a dynamic coefficient for correlation of input data. This way, input values can be pre-classified as grey values between 0 and 1 as they are normalized at same time. The results of machine learning algorithms with grey relational analysis with 12 features proves that data pre-processing and better feature extraction are both crucial for machine learning. When Table 4 and Table 5 are examined, it can be seen clearly that drop rates between training and testing have decreased dramatically. This shows that both features extraction and data preprocessing play important role on machine learning.

All these studies show that ensemble techniques such as bagging, boosting and stacking are best for imbalanced data. A powerful data pre-processing technique is also needed with better feature extraction method. Test results of ensemble classifier can be seen on confusion matrixes below. Figure 3 shows the result of ensemble classifier with six features extracted from raw data directly. Accuracy of the model is around 73% because of raw data with less features. Figure 4 shows the test result of ensemble classifier with more features extracted from this raw data directly. Six of these features are derivative values. Accuracy of the model is around 73% again because of raw data. There is no effective change in total accuracy. However, it can be seen that drop rate between training and testing has reduced because of derivative features.

This raw data contains corrupt and unnecessary measurement values. A grey relational coefficient has been determined to get rid of these measurement data. A new class has been created for this reason and labeled as zero class. All transient regime measurements of appliance have been ignored. This improve both training and testing accuracy ratings as can be observed in Figure 5 and Figure 6 below.

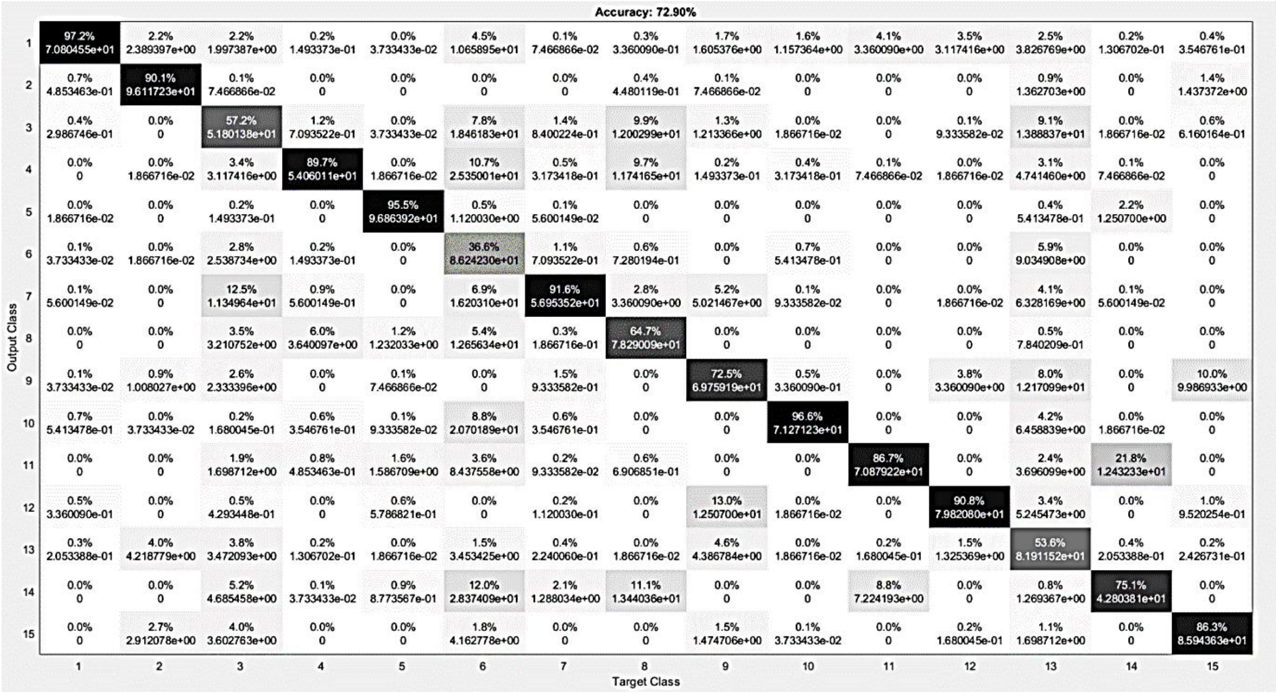

Figure 3. Test Result of Ensemble classifier with six features and raw data

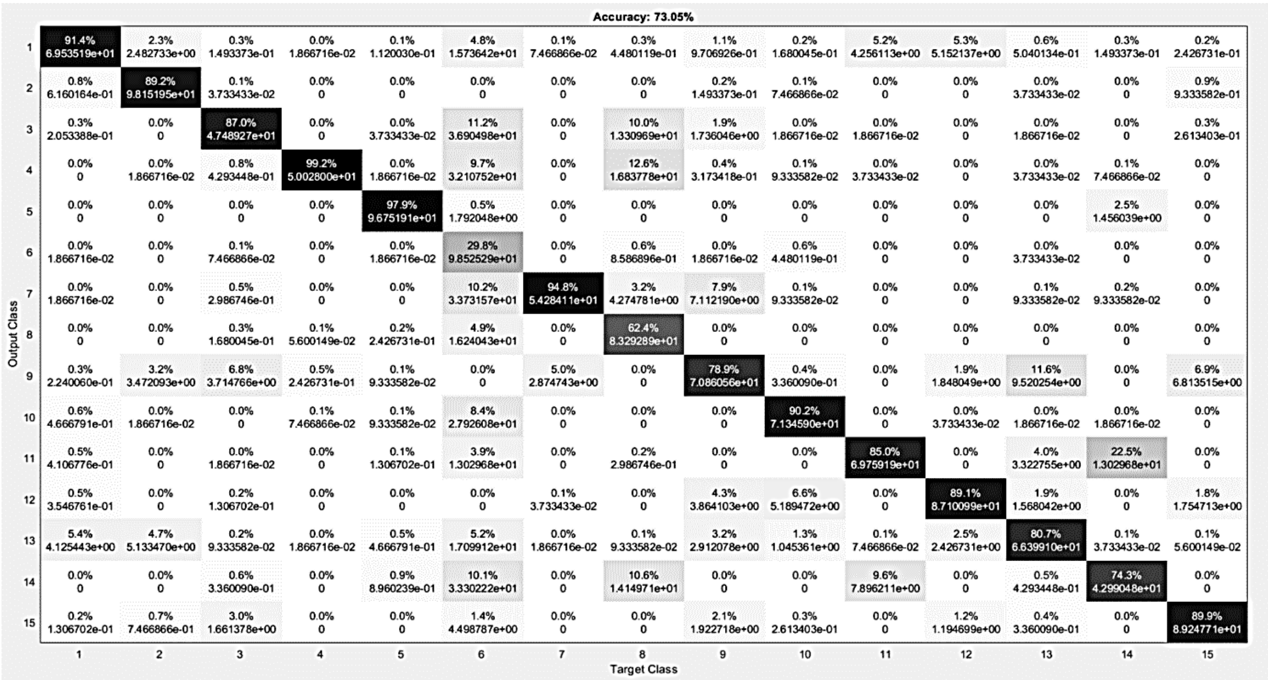

Figure 4. Test Result of Ensemble classifier with twelve features and raw data

It is obvious that feature extraction has positive effect on accordance between training and testing. On the other hand, it is necessary to use a data pre-processing technique for achieving better accuracy result. Figure 6 shows that GRA has increased the accuracy of the model dramatically. However, drop between training and testing is still high. Using more features to train the system will overcome this problem.

As it was presented before, the ensemble classifiers have the best accuracy rate in both training and testing data. The receiver operating characteristic (ROC) shows the performance of a classification model for each class [23]. The ROC curve has two parameters; true positive rate as in Equation (14) and false positive rate as in Equation (15). These parameters give proportional corellation of correct and false prediction of the model.

$$TPR = \frac{TP}{TP+FN} \quad (14)$$

$$FPR = \frac{FP}{FP+TN} \quad (15)$$

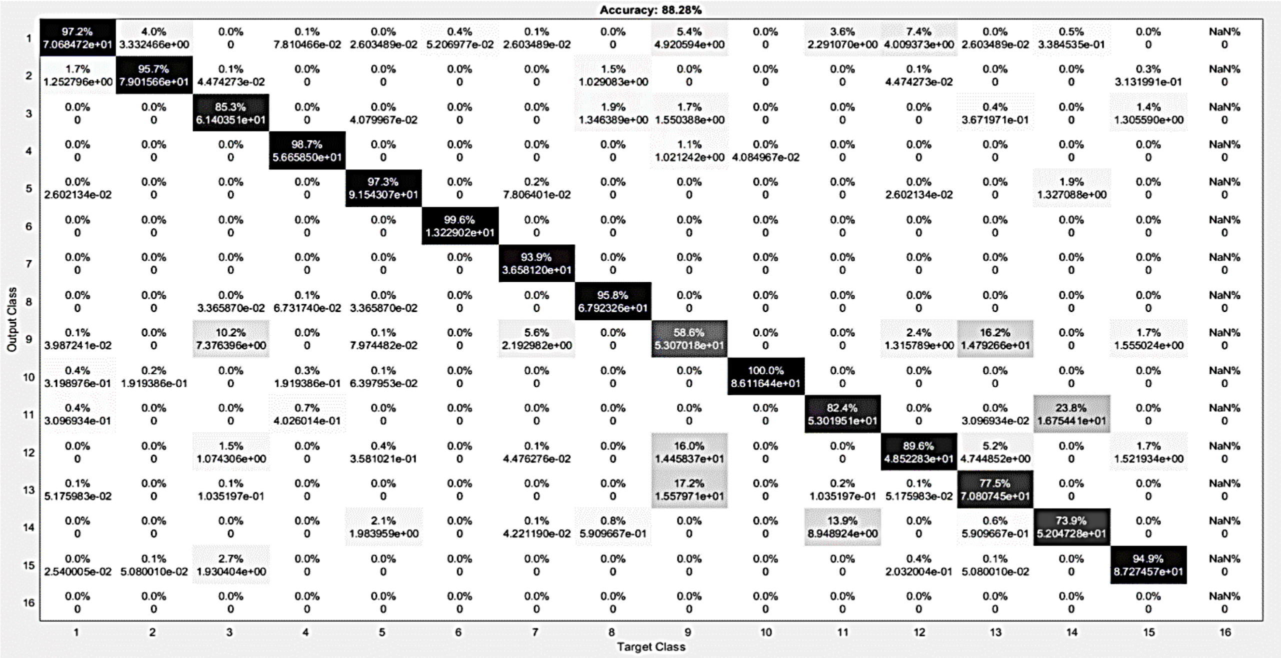

Figure 5. Test Result of Ensemble classifier with six features and GRA data

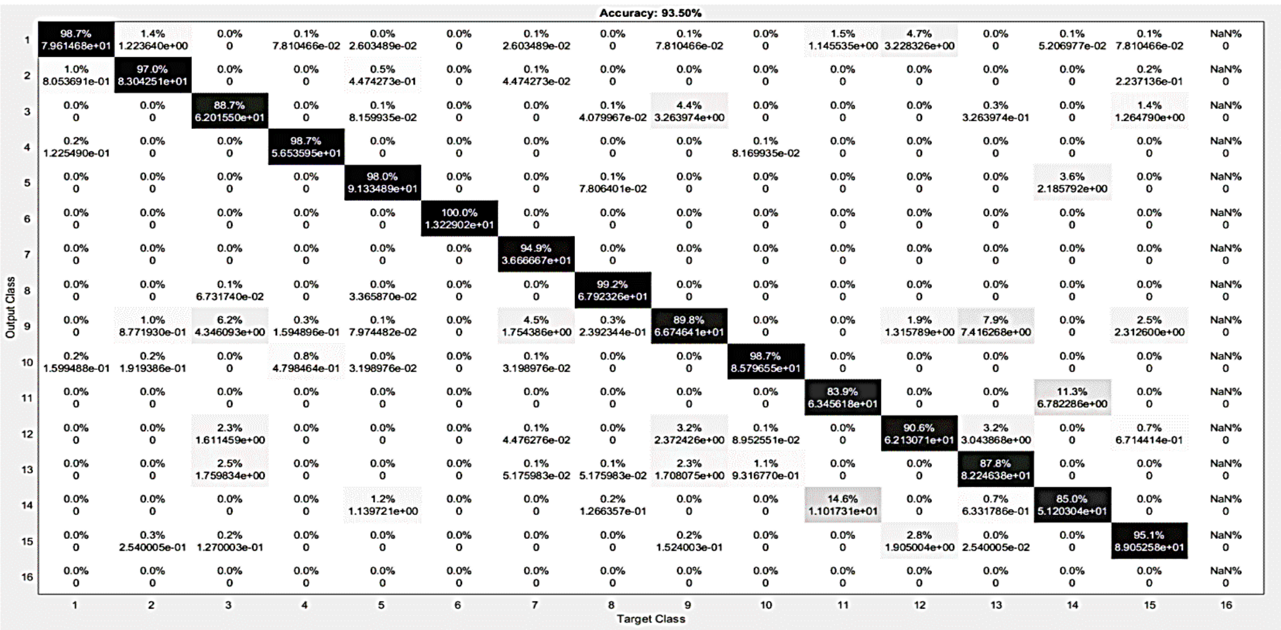

Figure 6. Test Result of Ensemble classifier with twelve features and GRA data

Where TPR is true positive rate, FPR is false positive rate, TP is true positive result, FP is false positive result, FN is false negative results and FP is false positive results.

Distribution of model prediction can be seen on Figure 7. The confusion matrixe show the detail of true and predicted classes on Figure 8 and Figure 9. Here, we create another class named zero. This class represent values which is no good for prediction because the appliance is neither in steady regime nor working at all. The GRA helps to detect these measurements and label them as class 0 at pre-processing. This way accuracy of the model has been increased.

The area under the ROC curve (AUC) represents the quality of the prediction model for each class independently. The AUC should be equal to 1.0 for perfect prediction rate. As it is shown on table 6, the ensemble classifier is highly successful on prediction for each class except for 14. Shaving machine has lower AUC value because it has low number of samples in the dataset.

Figure 7 shows correct prediction as dot and false predicton as cross sembol. It can be seen that some appliances have been mixed with others commonly when we examine the confusion matrixes in Figure 8. Especially, second matrixes in both Figure 8 and Figure 9 show how grey relational analysis improves the prediction quality by ignoring corrupt data.

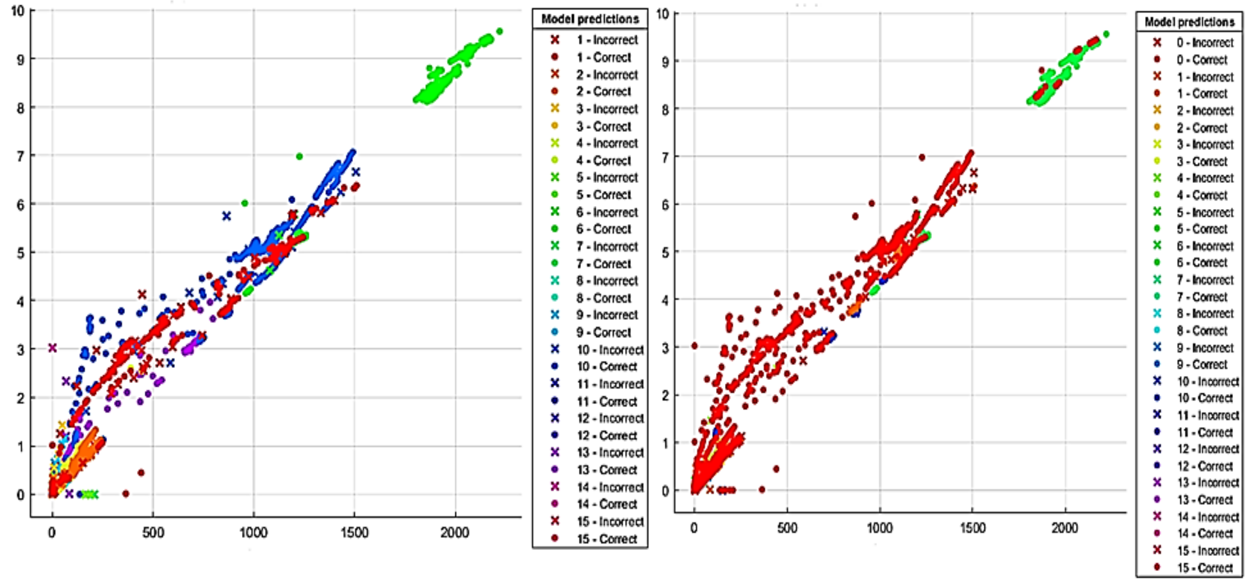

Figure 7. Distributions of prediction results (Raw data on left, GRA data on right)

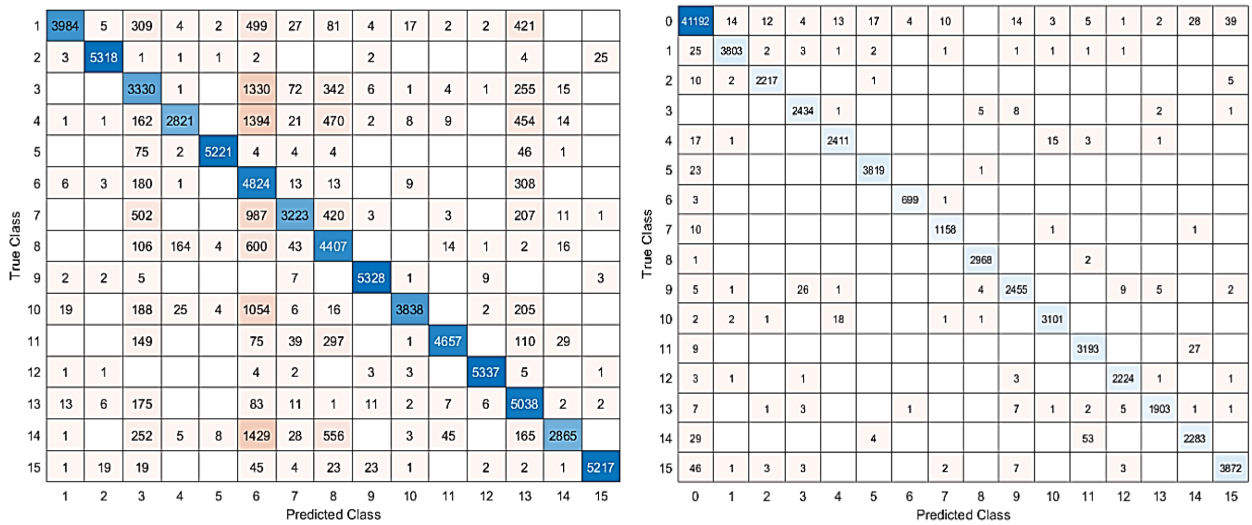

Figure 8. Confusion matrix for classes (Raw data on left, GRA data on right)

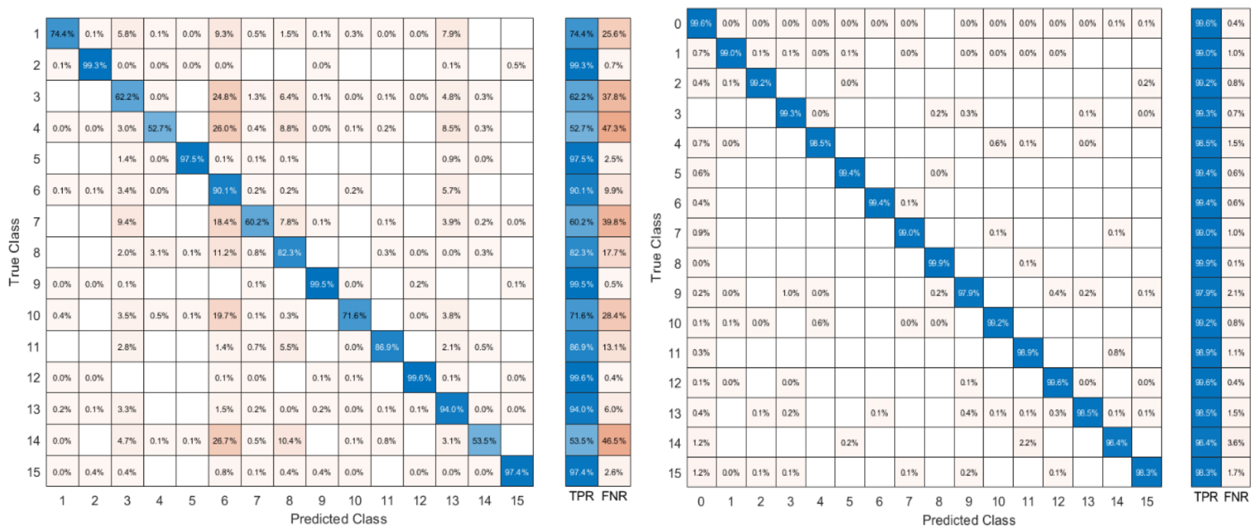

Figure 9. Confusion matrix for accuracy (Raw data on left, GRA data on right)

Table 6. ROC curve results for each class

Class	Label	AUC
1	Coffee Machine	0.990
2	Computer Station	0.992
3	Fan	0.993
4	Fridge and Freezer	0.985
5	Hi-Fi System	0.994
6	Kettle	0.994
7	Compact Fluorescent	0.990
8	Incandescent Lamp	0.999
9	Laptop Charger	0.979
10	Microwave Oven	0.992
11	Phone Charger	0.989
12	Monitor	0.996
13	Printer	0.985
14	Shaving Machine	0.964
15	Television	0.983

Table 7. Comparation with previous studies

Study	Pre-process	Classifier	Accuracy
Ridi [5]	Acceleration and Velocity	KNN GMM	83.1% 89.7%
Ruzzelli [6]	None	Bayesian Markov chain	84%
Mpawenimana [8]	Moving Average	KNN Random Forest	99.1%
Qaisar [9]	Compression Gain	Naïve Bayes	91.9%
Hamid [10]	NILM	Decision Trees	99%
This Study	GRA	Ensemble (Bagged Trees)	99.2%

4. Conclusion

It is important to pre-processes the data before machine learning. Better feature extraction is another important step to get best prediction results. A dynamic coefficient that shows the variant of the data would be used along with an effective normalization method. Previous studies show that data preparation techniques play important role in the results. Although, there are many different types of classifiers, each one has its own characteristic so they give different results with different dataset. The accuracy of studies which are presented in first section can be summarized as on Table 7. They all have used different pre-processing techniquies and classifiers but accuracy leves are varying.

In this study, grey-relational analysis has been used for feature extraction from ACS dataset. This quite improve the quality of data. In addition, measurement data have been filtered by removing inconsistent measurement values. Then different machine learning algorithms have been used for appliance recognition task by using only power parameters. Best result has been obtained by an ensemble (Bagged Trees) classification learner with 1% loss between training and testing phase. The confusion matrix shows that the most misclassification is on class 14 due to few measurement samples. Other than that, prediction model is highly accurate.

This study has demonstrated a supervised machine learning method with a different data pre-processing technique. Grey Relational Analysis can be used to analyze multivariable system. It normalizes the data while calculates the variation. Ensemble classification methods are best resulting machine learning algorithms. They are combination of different classification method with weighted voting algorithms. This method can be improved by implementing an artificial neural network which is another application of machine learning.

Declaration

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The author(s) also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

Y. Güven is responsible for all section of the study.

References

1. Zhaou, H. X., Magoules F., A review on the prediction of building energy consumption. Renewable and Sustainable Energy Reviews, 2012. **16**: p.3586-3592.
2. Lin, Y. H., Tsai, M. S., An Advanced Home Energy Management System Facilitated by Nonintrusive Load Monitoring with Automated Multiobjective Power Scheduling. IEEE Transactions on Smart Grid, 2015. **6**: p.1839-1851.
3. Sanchez-Sutil, F., Cano-Ortega, A., Hernandez, J.C., Rus-Casas, C., Development and Calibration of an Open Source, Low-Cost Power Smart Meter Prototype for PV Household-Prosumers, MDPI Electronics, 2019. **8**: p.878.
4. Medico, R., De Baets, L., Gao, J. et al., A voltage and current measurement dataset for plug load appliance identification in households, Nature Scientific Data, 2020. **7**: p.49.
5. Ridi, A., Gisler, C., Hennebert, J., ACS-F2 A new database of appliance consumption signatures. 6th International Conference of Soft Computing and Pattern Recognition (SoCPaR), 2017. **6**: p.145-150.
6. Ruzzelli, A. G., Nicolas, C., Schoofs, A., O'Hare, G. M. P., Real-Time Recognition and Profiling of Appliances through a Single Electricity Sensor. 7th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), 2017. **7**: p.1-9.
7. Huang, A. Q., Crow, M. L., Heydt, G. T., Zheng, J. P., Dale, S. J., The Future Renewable Electric Energy Delivery and Management (FREEDM) System: The Energy Internet, Proceedings of the IEEE, 2011. **99**(1): p.133-148.

8. Mpawenimana, I., Pegatoquet, A., Soe, W. T., Belleudy, C., Appliances Identification for Different Electrical Signatures using Moving Average as Data Preparation. Ninth International Green and Sustainable Computing Conference (IGSC), 2018. **9**: p.1-6.
9. Qaisar, S. M., Alsharif, F., An Adaptive Rate Time-Domain Approach for a Proficient and Automatic Household Appliances Identification. International Conference on Electrical and Computing Technologies and Applications (ICECTA), 2019, p.1-4.
10. Hamid, O., Barbarosou, M., Papageorgas, P., Prekas, K., Salame, C-T., Automatic recognition of electric loads analysing the characteristic parameters of the consumed electric power through a Non-Intrusive Monitoring methodology. Energy Procedia, 2017. **119**: p.742-751.
11. Khawaja, A.S., Anpalagan, A., Naeem, M., Venkatesh, B. Joint bagged-boosted artificial neural networks: Using ensemble machine learning to improve short-term electricity load forecasting, Electric Power Systems Research, 2020. **179**: p.1-7.
12. Himeur, Y., Alsalemi, A., Bensaali, F., Amira A., Robust event-based non-intrusive appliance recognition using multi-scale wavelet packet tree and ensemble bagging tree, Applied Energy, 2020. **267**: p.1-16.
13. Huchtkoetter, J., Tepe, M.A., Reinhardt, A. The Impact of Ambient Sensing on the Recognition of Electrical Appliances. Energies 2021. **14**: p.188.
14. Mihailescu, R-C., Hurtig, D., Olsson, C., End-to-end anytime solution for appliance recognition based on high-resolution current sensing with few-shot learning, Internet of Things, 2020. **11**: p.1-10.
15. Shin, E., Khamesi, A. R., Bahr, Z., Silvestri, S. and Baker, D. A., A User-Centered Active Learning Approach for Appliance Recognition, IEEE International Conference on Smart Computing (SMARTCOMP), 2020. p. 208-213.
16. Institute of Complex Systems [Cites 2020 11 June]; Available from: https://icosys.ch/acs-f2.
17. Zhang, S., Zhang, C., Yang, Q., Data preparation for data mining. Applied Artificial Intelligence, 2003 **17**(5-6): p.375-381.
18. Sallehuddin, R. Shamsuddin, S. M. H., Hashim, S. Z. M., Application of Grey Relational Analysis for Multivariate Time Series. Eighth International Conference on Intelligent Systems Design and Applications, 2008. **8**: p.432-437.
19. Voyant, C., Notton, G., Kalogirou, S., Nivet, M-L., Paoli, C., Motte, F., Fouilloy, A., Machine learning methods for solar radiation forecasting: A review. Renewable Energy, 2017. **105**: p. 569-582.
20. Mahdavinejad, M. S., Rezvan, M., Barekatain, M., Adibi, P., Barnaghi, P., Sheth, A. P., Machine learning for internet of things data analysis: a survey. Digital Communications and Networks, 2018. **4**(3): p.161-175.
21. Rahman, A., Tasnim, S., Ensemble Classifiers and Their Applications: A Review. International Journal of Computer Trends and Technology, 2014. **10**(1): p.31–35.
22. Kim, K-J., Cho, S. B., Ensemble classifiers based on correlation analysis for DNA microarray classification. Neurocomputing, 2006. **70**: p.187-199.
23. Machine Learning Crash Course [Cited 2020 2 February]; Available from: https://developers.google.com/machine-learning/crash-course
24. Tshitoyan V. [Cited 2020 27 April]; Available from: https://www.github.com/vtshitoyan/plotConfMat