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HOUSEHOLD ELECTRICITY CONSUMPTION PREDICTION AND ANOMALY DETECTION BASED ON FEATURES USING TWO-STEP UNSUPERVISED DEEP LEARNING APPROACH

S. A. A. Rauf*[1], A. F. Adekoya[1], P. Mensah[1] and P. Nimbe[1]

[1] Faculty of Computer Science, University of Energy and Natural Resource, 214, Sunyani Ghana, West Africa.

*corresponding: rauf.seidu.stu@uenr.edu.gh

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Abstract— Accurate prediction of household electricity consumption is significant as it serves as a building block for effective energy management and operational decisions, essential for curtailing non-technical losses. A range of machine learning techniques have been implemented for detecting abnormal electricity consumption and have achieved significant results. However, with the evolution of anomalous electricity consumption coupled with the rapid growth in electricity consumption data, new challenges confronting anomalous electricity consumption are emerging. This current

Consumption	study proposes a two-step unsupervised machine learning approach, including a gated recurrent unit (GRU) regular network and a gated recurrent unit (GRU-autencoder) autoencoder, to detect consumption anomalies. The analysis was based on data collected from 450 households over a three-month period within the Tamale municipal assembly. The performance of the proposed model (the GRU autoencoder) was estimated using the MSE value, f-score, precision, and accuracy. The GRU autoencoder outperforms state-of-the-art methods in detecting anomalous electricity consumption, achieving an accuracy of 90.97% on the trained dataset.

I. Introduction

Electricity has remained the beacon to growth in modern-day industrialization. The normal and efficient usage of electricity is an ultimate target by nations in the case of limited resource for effective development [1]. However, this is difficult to achieve due to losses from both technical and non-technical issues. Technical losses occurs from the transmission and distribution of electrical power through power lines and other electrical equipment due to resistance in wires, transformer inefficiency and other technical challenges [2]. Non-technical losses are electricity end-user behavioral-related factors such as the usage of faulty electrical appliances, forgetting to switch off appliances, unauthorized use, over-lighting or usage of electrical units, energy leakage, and power theft [3]. These losses or anomalous consumption have great financial burdens on the end-user, utility providers, and the nation as a whole. For instance, a sum of over $102 billion are lost annually across 138 countries [4] and nearly 50% of electricity generated in developing countries cannot be accounted for due to non-technical losses [2].

Various big data analytic tools and machine learning techniques have been implemented by researchers to detect anomalous electricity consumption. This help to improve energy efficiency and guarantees the normal operation of electrical units [5][6]. However, they do not consider the consumption patterns of electricity. To further improve the accuracy and efficiency of anomaly detection techniques, the current study implements a two-step unsupervised deep learning approach, including the Gated Recurrent Unit (GRU) regular network and the Gated Recurrent Unit Autoencoder (GRU-autoencoder), to predict household consumption, learn the normal consumption patterns, and predict any anomalous consumption based on features from different categories such as lifestyles or consumer behaviors, socio-demographics, technology, and appliance features. The contributions of this current study are stated as follows:

1. The household lifestyle and the lag variables enhanced the GRU autoecoder achieving an accuracy of 90.97%.
2. The GRU regular network predicted the household electricity consumption one hour ahead for the GRU autoencoder to learn the normal consumption improving its accuracy for the anomaly detection.
3. Based on the learned attributes of the household normal consumption, the detected anomaly is localized into extrema (global-37.56%) and non-extrema (local-90.76%) using the reconstruction error. The high value of the non-extrema (local) demonstrates the success of the GRU autoencoder.

II. Literature Study

In recent years, electricity consumption anomaly detection has received a lot of research attention. Various diverse approaches have been introduced and implemented to detect abnormal electricity consumption. These approaches can be categorized into statistical [7], machine learning [6], and deep-learning based methods [8]. The statistical analysis of abnormal electricity consumption is rule-based.

The statistical technique considers the normal consumption of electricity in certain patterns or distributions, and any deviation from these patterns or distributions is marked as abnormal consumption. Statistical metrics such as mean, percentiles, median, and standard deviations are the computational tools used to identify the data point outside its expected range. For instance, the Generalized Extreme Studentized Deviate (GESD) and the Canonical Variate Analysis (CVA) is implemented to identify the variables of daily electricity consumption and detect any anomalous consumption [9]. The autoregressive moving average (ARIMA) is implemented to validate anomalous electricity consumption in the case where readings from smart meters are altered to steal electricity [10]. In the case of complex anomalous electricity consumption patterns, statistical analysis is not an ideal technique due to its computational complexity and assumptions.

The traditional machine learning techniques implement mainly the traditional machine learning models, such as decision trees [11], support vector machines [12], principal component analysis [10] and K-nearest neighbors [13] to learn the normal electricity usage patterns and predict any form of deviation as anomalous. The traditional machine learning models have gained popularity in recent years in anomalous electricity consumption detection due to their improved performance in abnormal detections, scalability, and robustness. They can automatically analyze the streaming dataset and identify any breach in the data to detect any anomalies. Critical incidents such as fraud, intrusion, and technical breaches can easily be noticed, and concerned parties are automatically alerted to remedy the situation as compared to the statistical analysis methods [14]. However, it requires further improvement in terms of detection accuracy since it is largely dependent on feature engineering.

The deep learning models, on the other hand, can learn from any complex and nonlinear correlation in large data sets automatically and predict any form of anomaly. For instance, hybrid convolutional neural network with a random forest is implemented to detect any form of electricity theft automatically [15] while a hybrid bi-directional gated recurrent unit (GRU) and bi-directional long-short-term memory (LSTM) are implemented for electricity theft detection [7]. A study by Niccolo Zangrando *et al.* utilized both the LSTM and the CNN to detect any form of electricity fraud [1]. However, there is a need for more accurate and efficient techniques for electricity anomalous detection to improve energy efficiency and relieve consumers and utility providers of the financial burdens accrued from anomalous consumption.

III. Methodology

This section presents the methods adopted for the implementation of the proposed household electricity consumption anomaly detection based on features using a two-step deep learning approach.

A. Gated Recurrent Unit (GRU) Regular Network

The GRU, as presented in the work of [7], the GRU identifies the dependent variables at time intervals and solves the problem of vanishing gradients. The advantages of the GRU over LSTM (long short-term memory) are a simpler structure with less computational power and faster training time due to missing memory cells [7]. GRU consists of two gates which are one gate for resetting, H, and the other gate for updating, Z. The reset gate, H, is a merger of the memory state and the hidden state, while the updating gate, Z, is a merger of the input gate and the forget gate. The rest gate, H, can be determined as Equation (1).

$$H = sig\left(WH \cdot C_{t-1} + RH_{\cdot x_t}\right) \quad (1)$$

The update gate, Z can retain precious knowledge, periodically update the content and carry it forward. It can be computed by Equation (2).

$$Z = sigmoid\ function(W_Z C_{t-1} + R_{zxt}) \quad (2)$$

The new memory that emerged in the GRU cell is based on new input and the previous hidden state. The new gate can eliminate the previous hidden state if it is detected to be irrelevant. This can be computed by Equation (3) and (4).

$$M = tanh\left(W_M(C_{t-1} * H) + R_{Mx_t}\right) \quad (3)$$

$$C_t = (C_{t-1}) * (1 - Z) + Z * M (4)$$

where, W is weight metrics, R is parameter vector, x_t is input, C_t is current output and C_{t-1} is previous output. The structure of the GRU is illustrated in Figure 1. Unlike where traditional Recurrent Neural Networks (RNN) replace the content by adding new value, the GRU keeps the original content and updates the information to make it more accurate.

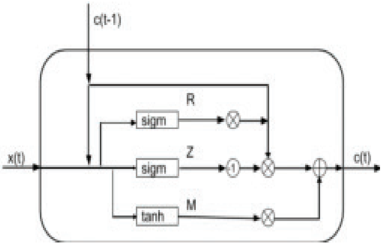


Figure 1: Structure of GRU

B. Gated Recurrent Unit (GRU) Auto Encoder Network

The GRU auto encoder consists of two modules which are encoder and decoder. The data is inputted into the encoder for its features to be learned in a reduced dimension. The decoder will reconstruct the original data for effective features like the original input data. Figure 2 illustrates the auto encoder modules.

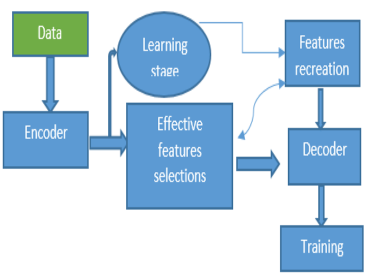


Figure 2: GRU auto encoder module illustration

C. Training the GRU Auto Encoder

The processes by which the GRU auto encoder is trained to reconstruct the original input data are summarized as follows:

1. The data goes into the encoder from high dimensional input to a bottleneck layer where important features are extracted, and the input data is compressed reducing the data dimensions due to the number of neurons.
2. The decoder reconstructs the original input data from the compressed input data.
3. The GRU auto-encoder network repeats these steps until the network can reconstruct the best original input from an "encoded" state.

When the data is reconstructed, we can compare the reconstructed data with the original input data to determine the reconstruction error and losses. Figure 3 illustrates the auto-encoder network architecture.

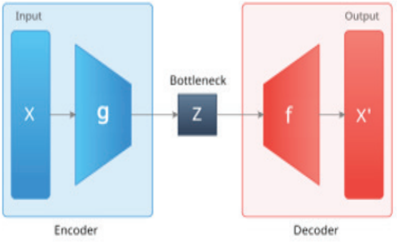


Figure 3: the auto encoder network architecture

The GRU auto encoder network loss function is determined by Equation (5).

$$L(\emptyset,\theta) = \frac{1}{N}\sum_{i=1}^{N} x^i - f_\theta(g_\emptyset(x^i)))^2 \quad (5)$$

Equation (5) is the sum-up difference between the original data *(x)* and the reconstructed data $(f_\theta(g_\emptyset(x^i)))$. The $\emptyset, \theta$ are parameters that define the encoder and decoder which the loss function depends on. The encoder and decoder are represented by $g_\emptyset$, f_θ respectively whiles x^i is the i^{th} feature and *N* being the number of input features. Figure 4 illustrates the procedure for the reconstruction error determination.

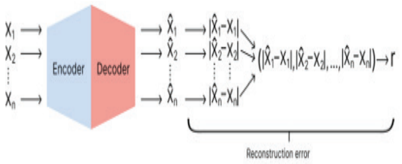


Figure 4: Reconstruction error determination

D. Model Design Specification

Figure 5 illustrates the conceptual framework of the proposed model.

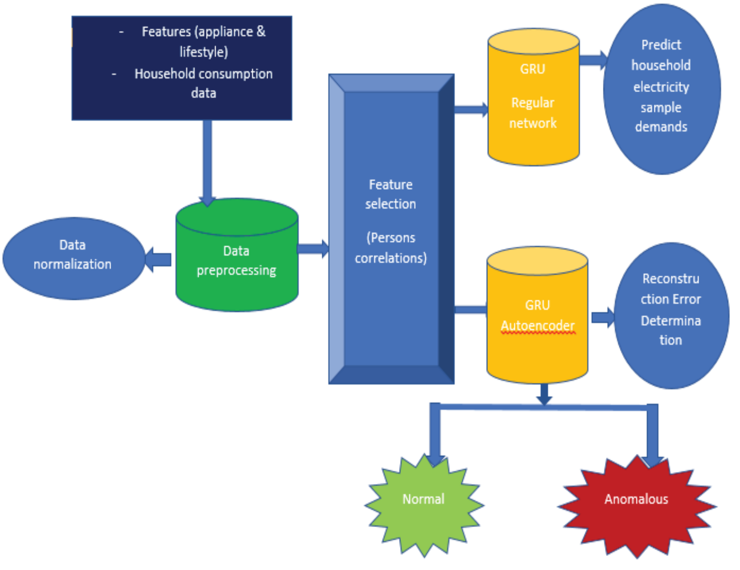


Figure 5: Proposed model conceptual framework

The model design steps are outlined as follows:

1. The data preprocessing includes normalization and feature selection as Equation (6).

$$R' = \frac{R-\mu}{\sigma} \quad (6)$$

where, σ is the standard deviation of features values, R is the features matrix's values, R^t is the normalized features values matrix and μ is the mean values of the features.

2. The household normal electricity consumption data is then used to train the GRU autoencoder network. It learns the attributes of the household's normal consumption and then reconstructs the instances of normal time series. This gives the GRU autoencoder the ability to determine the

instances of the time series being normal or anomalous.

3. The performance of the proposed model is evaluated using the Mean-Square Error (MSE), Precision, Recall, False Positive Rate (FPR) and F-score. They are calculated using Equation (7).

$$MSE = \frac{1}{n}\sum(actual\ (Y_i) - forecast\ (Ý_i))^2 \quad (7)$$

where, MSE is the mean square error.

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive + False\ Positive\ (FP)} \quad (8)$$

$$Recall\ Value = \frac{True\ Positive\ (TP)}{True\ Positive + False\ Negative\ (FN)} \quad (9)$$

$$FPR = \frac{False\ Positive\ (FP)}{True\ Negative\ (TN) + False\ Positive\ (FP)} \quad (10)$$

$$Fscore = \frac{Precision * Recall}{Precision + Recall} * 2 \quad (11)$$

E. Experimental Setup

A semi-structured questionnaire approach was used to design 15 sets of questions to obtain the features from participants. The questionnaire was structured to obtain features from participants' lifestyles, socio-demographics, and household appliance consumption. A total of 450 households were randomly selected, and the questionnaire was administered in 8 different communities within the Tamale municipal assembly. The received responses were queued in Microsoft Excel in comma-separable values (CSV) file format. The implementation was done with Kera, a Python-based deep-learning library. The input data was structured uniquely since there was no flexibility with network information in the Kera network architecture. The dataset was split into 80% for training and 20% for testing.

F. Anomaly Localization

Anomalous observations that are present in the time series and have been identified are localized using the reconstruction error. The anomalous observations in the time series stamps are distinguished between extrema (global) anomalies and non-extrema (local) anomalies.

IV. Result and Discussion

Helpful engineered features that best describe time series-based datasets are collected. Figure 6 depicts households' electricity consumption with the y-axis indicating the electricity demand and the x-axis for the date. It can be observed clearly in the daily and weekly electricity consumption patterns, high demand for electricity during the weekdays with lesser electricity consumption on the weekends. Figure 7 clearly indicates the total annual demand pattern of the households. From Figure 6 and Figure 7, it can be concluded that the hours of the day, days of the week and months of the year features have a great influence on household electricity consumption and hence are significant features to consider.

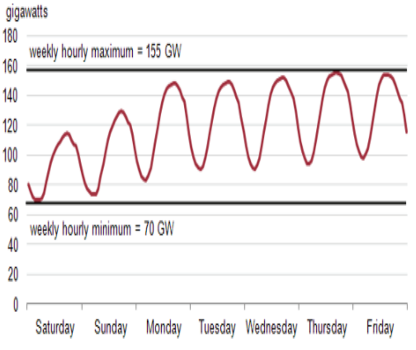


Figure 6: Weekly household electricity demand patterns

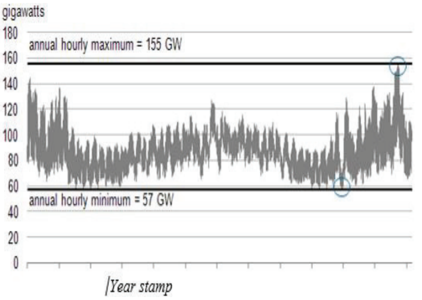


Figure 7: Annual household electricity demands pattern

A. Features Selection

The strength and direction (weakness) of the variables used for prediction in the consumption data are measured using Person Correlation Coefficient (PCC). It is a range between -1 and +1 that measures the strength. This can be calculated using Equation (12).

$$r = \frac{\sum(x_i - x^-)(\ y_i - y^-)}{\sqrt{\sum(x_i - x^-)\sum(\ y_i - y^-)}^2} \qquad (12)$$

where r is the person correlation coefficient, x_i and y_i is the value of x and y variables in the data samples, x^- and y^- are the mean values of x and y variables.

A value of 0 indicates no correlation between electricity consumption and a particular variable hence deleted due to irrelevance. A positive value greater than 0 shows a correlation between the consumption and the variable while less than 0 indicates a negative strength and direction of the consumption and the variable. It can be strongly argued from Figure 8 that there is more than one variable that affects electricity consumption demands. Features such as the brand of the oven, TV color, temperature set for air-conditioners, average monthly load and average year load are not included in the training phase due to low correlation with electricity demands.

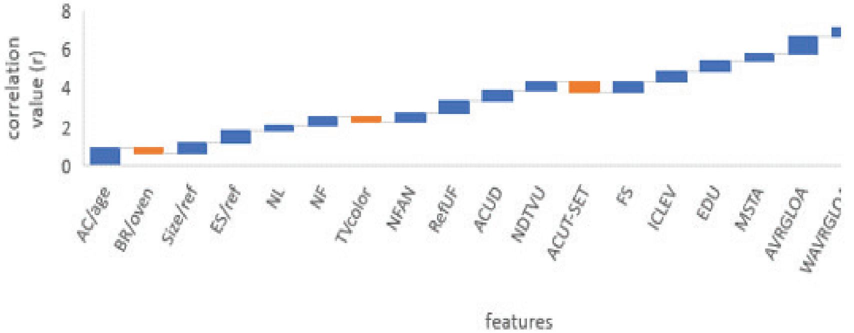


Figure 8: Person correlation between anomaly detection predictive variables and electricity demands

B. Evaluation Threshold

Different thresholds were quantitatively analyzed against performance measures to learn the threshold that identifies anomalies. Precision, recall and f-score performance measures were calculated. The varied threshold value was in a range of -35 to -5 to calculate the value of precision, recall and f-score based on log-likelihood. If an observation $X(t)$ has a value greater than the threshold then it is considered as normal otherwise anomalous if it is less than the threshold value. The classification was done based on Equation (13); for any given observation $X(t)$: if

$$X(t)\epsilon(\mu + 3\sigma, \mu - 3\sigma) \qquad (13)$$

Then it is classified as anomalous belonging to the positive class. The GRU auto-encoder performs better with precision, recall and Fscore with different threshold values. The threshold value that well-utilizes the Fscore was found to be -14.71. Figure 9 shows the precision performance measure against different thresholds values.

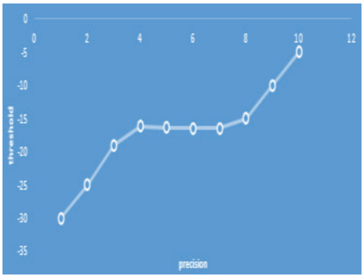


Figure 9: Precision performance measure against different thresholds values

C. GRU Auto Encoder for Anomaly Detection

The GRU autoencoder trained on the dataset was implemented with a network architecture of 2-hidden layers. The first hidden layer with 40 units and the second hidden layer with 20 units. It has a single neuron output layer with a linear activation function. The GRU network was trained with a stochastic algorithm (the Adaptive Moment Optimizer-Adam optimizer) to optimize its loss function. The Adam Optimizer updates the parameters to reach the optimal local minimum value (learning rate = 0.01) for 68 samples processed (batch size = 68) with 300 complete passes through the training dataset (epochs=300).

Training the GRU network with the optimizer stops at the sixth iteration (patience=6) when the validation error is no longer decreasing anymore. The model gave an MSE value of 0.061, Table 1 summarizes the parameters of the GRU autoencoder and results obtained for anomaly identification. Figure 10 shows True anomaly detection regions.

Table 1: Prediction model specification and results for anomaly identification

Model	GRU Auto-encoder	
	Type / Train (%)	Weight / Test (%)
Network architecture	Layer 1 =	40
	Layer2 =	20
Parameters	Learning rate =	0.01
	Patience =	6
	Epoch =	300
	Batch =	68
	Optimizer type	Adam Optimizer
MSE	0.405	0.611
Precision	97.63	61.37
Recall	84.32	85.37
F-score	90.33	71.40
Accuracy	90.97	88.68

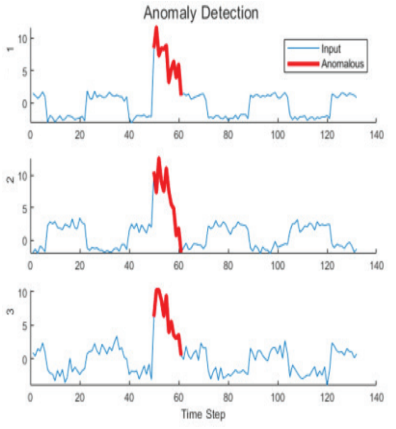


Figure 10: True anomaly detection regions

The prediction accuracy of the GRU autoencoder was observed to be significantly good (90.97% on the training dataset and 88.68% on the test dataset) with a relatively high MSE value. A lower MSE value of a model indicates good performance. The relatively high value of the MSE could mean that the training and testing dataset contains some anomalies in which the GRU autoencoder can learn the normal characteristics of the data and outputs values that conform to the normal characteristics of the data resulting in high predictive errors at the instance of anomalous behavior. The GRU autoencoder model performs better on precision, recall and Fscore metrics. It can be observed from Figure 10, how the GRU autoencoder model tries to predict the missing weekday's peak based on normal weekly patterns. It can remember the weekly consumption patterns and builds memory for all previous observations across batches.

The following steps were implemented to identify anomalies based on the reconstruction error.

1. The study calculated the reconstruction error for each sample in the time series to determine the anomalies.
2. The time series are monitored to determine the mean, μ, and standard deviations, σ, over the metrics.
3. Deviation distance from the metrics average is calculated by $(\mu \pm 3\sigma)$. This measure how far the standard deviation is from the average of the metrics.
4. The threshold of anomaly detector was determined using exponential moving average (EMA).

5. The observations were then classified as anomalous or normal.

The anomalous identified in the observations were also localized based on extrema (global) anomalies or non-extrema (local) anomalies.

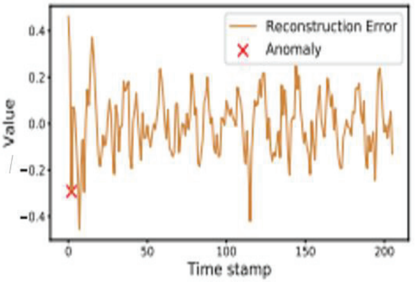
D. Anomalies Localizations Identification

A dummy approach is used by taking the argmax of the time series observations as a located anomaly. The current study distinguishes between the anomalies as extrema (global) and non-extrema (local), and the results obtained on all types of anomalies based on quality assessments are shown in Table 2.

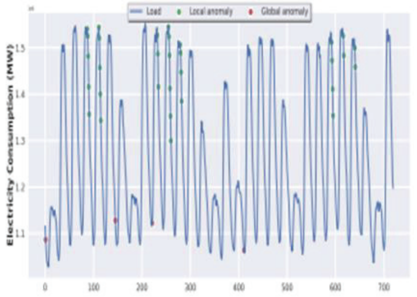
Table 2: Anomalies localization result for the two identified anomalies; extrema (global) and non-extremer (local)

dataset	Accuracy (%)		Precision (%)		Recall (%)		F-score (%)	
	Non-extrema (local)	Extrema(global)	Non-extrema	extrema	Non-extrema	extrema	Non-extrema	extrema
training	90.76	37.56	90.71	40.62	90.76	37.57	90.78	38.21
testing	94.45	28.74	94.75	32.80	94.73	28.74	94.82	28.36

From Figure 11 (a), the reconstruction error is indicated with the brown color with an identified anomaly in the dataset being marked as red-cross (x) and in Figure 11 (b), the identified anomalies are localized into global and local.



(a)



(b)

Figure 11: (a) identified anomaly against reconstruction error, (b) location of the identified anomalies

The blue strips represent the predicted demands, the green-dot indicates the global anomaly whiles the orange dot indicates a local anomaly. The evaluation of the results obtained indicates that the household lifestyle and lag features have greatly added an improvement to the efficiency of the model in identifying anomalies in data due to the dynamic lifestyle of household occupants' electricity consumption. Figure 12 presents a comparison between normal and abnormal consumption patterns of households.

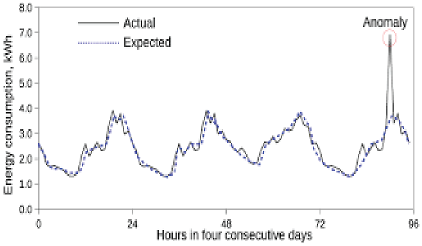


Figure 12: Comparison of normal and anomalous electricity consumption

E. Comparison with Previous Methods

The outcome of the current study was compared with El Hadad *et al.* [8], Wang *et al*. [16] and C. Huang *et al*. [17] with the same experimental dataset. El Hadad *et al.* implemented a random forest (RF) with one iteration in detecting anomalies in household electricity consumption. Wang *et al*. Implemented SVM multiclass with radial basis function kernel while C. Huang *et al.* employed logistic regression on feature samples to detect anomalies in residential consumption. Osegi *et al*. used Hierarchical Temporal Memory (HTM) spatial pooler to predict short-term load by forming sparse distributed representation (SDR) from a univariate load time series data. The SDR is transformed using temporal aggregator in to sequential bivariate representation space and an overlap classifier makes temporal classifications from the bivariate SDR through time [18]. Our proposed model outperformed the previous methods. Table 3 summarizes the results of the comparison.

V. Conclusion

The performance of the proposed model (GRU Autoencoder) was evaluated using MSE value, F-score, precision, and accuracy. The GRU autoencoder obtained an MSE (0.045), precision (97.63%), f-score (90.33%), and 90.97% accuracy as compared to MSE (0.511), precision (90.21%), F-score (88.57%), and 90.02% accuracy for random forest (RF), MSE value

(0.467), precision (94.53%), f-score (89.59%), and 90.15% accuracy for logistic regression (LR), and MSE (0.431), precision (96.84), F-score (90.15%), and 90.45% accuracy for support vector machine (SVM) on the training dataset, indicating a better fit as compared to the other models. Additionally, it was observed that household lifestyle and the lag variables have enhanced the performance of the GRU autoencoder in detecting anomalies in household energy consumption. In the future, different methods can be proposed to evaluate the performance of anomaly detection techniques with a more diverse approach in terms of data labeling. The addition of data labeling is likely to enhance the quality and accuracy of the anomaly detection technique.

Table 3: Model comparison with previous methods for anomaly identification

Model	Model Evaluation									
	MSE (%)		Precision (%)		Recall (%)		F score (%)		Accuracy (%)	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
GRU Autoencoder (propose)	0.405	0.611	97.63	61.37	84.32	85.27	90.33	71.40	90.97	88.68
Random Forest (RF)	0.511	0.723	90.21	57.63	81.77	82.69	88.57	65.76	90.02	86.71
Logistic Regression (LR)	0.467	0.657	94.53	59.52	83.41	82.74	89.59	68.71	90.15	87.49
Support Vector Machine (SVM)	0.431	0.634	96.84	59.72	83.92	83.55	90.15	69.83	90.45	87.62
Hierarchical Temporal Memory (HTM)	0.418	0.628	97.21	60.45	84.15	84.33	90.25	70.43	90.77	88.29

VI. Acknowledgement

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