



## ARTIFICIAL INTELLIGENCE - DRIVEN ANOMALY DETECTION IN ENERGY SYSTEMS

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### Abstract

Enormous amounts of data are being produced everyday by sub-meters and smart sensors installed in residential buildings. If leveraged properly, that data could assist end-users, energy producers and utility companies in detecting anomalous power consumption and understanding the causes of each anomaly. This research focuses on the use of AI for anomaly detection in energy systems, specifically targeting Central Processing Unit (CPU) and Graphic Processing Unit (GPU) overheating in energy systems. With the increasing complexity and reliance on energy-consuming devices, overheating can significantly affect system performance and energy efficiency. This research proposes an artificial intelligence driven model integrated into the task scheduler of a system to monitor CPU and GPU temperature levels. When abnormal temperature thresholds are detected, the system promptly alerts the user, preventing potential damage and ensuring optimal performance. The methodology follows a structured approach which is the Cross-Industry Standard Process for Data Mining

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(CRISP-DM) framework, using Python programming and leveraging task scheduling for real-time monitoring. The results highlight the model's accuracy in detecting anomalies, providing timely alerts, and preventing overheating events. The anomaly detection system improves energy management by identifying potential risks before they escalate, demonstrating its ability to optimize system efficiency, reduce energy waste, and improve decision-making regarding system and sustainability.

## 1. Introduction

The increasing urgency of climate change and the global reliance on non-renewable energy sources underscore the need for more efficient energy management practices. In particular, the building sector accounts for over 40% of global energy consumption and contributes to more than 30% of CO<sub>2</sub> emissions worldwide [1]. The increasing energy consumption of buildings is also because most buildings are not performing as expected by their designers/managers. These levels of consumption, driven by the need for heating, cooling, and appliance usage, significantly strain energy resources and lead to wasteful emissions [2]. Reducing energy consumption in buildings has therefore become a critical goal for environmental sustainability, one that is increasingly pursued through innovative, data-driven technologies. Projections considering current energy policies demonstrate that global electricity consumption will grow by 84% in next 25 years [3, 4]. Information and Communication Technologies (ICT) are an essential means by which energy efficiencies may be achieved. However, consumers and even managers are still hesitant to widely adopt ICT technologies that contribute to energy efficiency for many and diverse reasons such as (i) the lack of demonstration of their cost-effectiveness (ii) the current under-development of applications that exploit energy usage data for the benefit of consumers and designated third parties (iii) The lack of demonstration that energy savings can be achieved without compromising comfort levels and (iv) Limitations on consumers' capacity or capability to make the necessary changes in energy usage habits [5-7].

Traditional methods of managing energy efficiency often focus on promoting user awareness and introducing energy-saving appliances. However, a more advanced approach has emerged: leveraging artificial intelligence (AI) for real-time monitoring and anomaly detection in energy systems. AI-driven anomaly detection is a cutting-edge approach that uses machine learning algorithms to identify unusual patterns in energy usage, helping to spot irregularities that might indicate waste, malfunction, or inefficient energy use. These anomalies may include instances such as unnecessary usage, appliance faults, or abnormal energy patterns that deviate from a building's typical energy profile [8, 9]. Anomaly detection in energy systems relies on AI models capable of monitoring consumption data in real-time and detecting deviations that could indicate wasteful behavior or potential failures. For example, an AI model can identify when an appliance is consuming more energy than usual,

perhaps due to wear or misconfiguration, and alert the building manager or homeowner [10]. Indeed the building energy sector is responsible for almost 40% of energy consumption and up to 45% of CO<sub>2</sub> emissions around the globe [11]. This approach supports not only conservation efforts but also contributes to the safety and longevity of appliances. AI-based detection models can further differentiate between genuine needs for energy and wasteful practices, such as appliances left running without purpose or air conditioning systems operating while windows remain open [12-14].

AI-driven anomaly detection systems offer notable advantages over traditional energy management approaches. They allow for scalable, continuous monitoring, which is crucial in large buildings with complex energy systems. By using advanced algorithms like clustering, neural networks, and dimensionality reduction techniques, these systems can effectively distinguish between normal and abnormal consumption patterns and provide tailored feedback to end-users [15]. Recent advancements in anomaly detection, including the use of unsupervised learning algorithms, make it possible to identify anomalies even without labeled data, making the solution applicable to diverse and dynamic environments. The growing adoption of AI in anomaly detection aligns with governmental and organizational goals to reduce energy waste and improve sustainability. The European Union has set significant challenges for energy and climate policy, such as the 40/27/27 objectives (40% increase in energy efficiency, 27% reduction CO<sub>2</sub> emissions, and 27% integration of renewable energies by 2030 [16, 17]). Many national and regional policies now encourage energy efficiency and support AI-enabled technologies in the building sector. As these systems gain traction, they also introduce additional considerations, such as data privacy, real-time scalability, and user adoption. However, the potential for AI-driven anomaly detection to transform energy management and contribute to environmental sustainability is substantial, paving the way for smarter, greener buildings that minimize waste and promote efficient energy usage [18-20].

## 2. Related Works

AI is currently being implemented in detecting anomalies in energy systems within buildings using advanced methods like deep learning, time-series analysis, and graph-based techniques [21]. These systems focus on identifying deviations in energy usage patterns caused by faults, inefficiencies, or irregular behavior, thus improving energy efficiency and preventing equipment failures. One significant implementation involves deep learning techniques such as convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) to analyze large-scale, high-dimensional energy datasets [22-24]. These models extract intricate patterns from time-series data and predict anomalies before they cause significant disruptions. For instance, researchers have combined Transformer architectures with generative adversarial networks (GANs) to improve anomaly detection in

power distribution systems, achieving high accuracy and robustness in identifying unusual energy usage [25-28]. Another innovative approach is the use of graph-augmented normalizing flows that integrate sensor dependencies within buildings to model complex relationships in energy data. This method outperforms traditional rule-based or statistical anomaly detection systems by using Bayesian networks to identify low-probability events effectively, like sudden voltage spikes, without predefined rules [29, 30]. AI implementations also include unsupervised clustering and dimensionality reduction techniques for detecting anomalies in unlabeled datasets. These methods are particularly useful in analyzing energy consumption patterns influenced by factors like occupancy and environmental conditions. Additionally, privacy-preserving measures and real-time detection capabilities are being integrated into these systems to enhance their applicability in modern smart building environments [31-32].

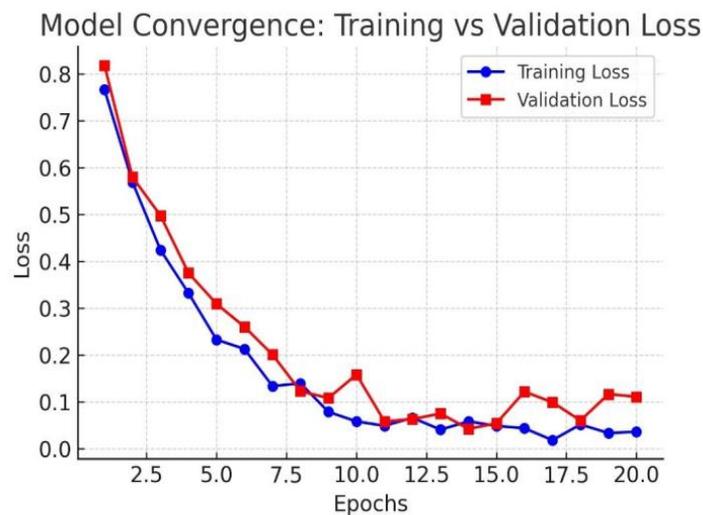
Haque et al. [32] proposed a unique intrusion detection method combining two machine learning techniques: autoencoder (AE) and one-class support vector machine (OCSVM) to detect anomalies in smart building sensor measurements. While the AE does well in lowering false alerts, it fails to detect some anomalous samples. The OCSVM model on the other hand, detects anomaly effectively but raises a lot of negative alarms. The combination of the benefits of these models gave a 99.6 F1-score. Spatial-temporal graph conditionalized normalizing flows (STGNFs) by Zhang et al. [19] interleaved multiscale dilation convolutional layers with mix-hopping graph convolutional layers to form a spatio-temporal feature extractor. Then the features were employed as the information for NF and the variables factored in for operating conditions change, Interpretable AD findings can then be obtained by following the anomalous variables via the conditional density magnitude. Lastly, the performance of STGNF is illustrated by experimental findings on four datasets, including real nuclear power plant data and high-fidelity experimental bench data. Beyond the constraints of current techniques, STGNF allows for the detection and accurate localization of abnormalities in a variety of power modes, including nuclear plant shutdown and peaking.

Borda et al. [33] developed both supervised and semi supervised models. The Artificial Neural Network (ANN) was used to capture non linear relationships among features, detecting simultaneous faults in a heating, ventilation and air conditioning (HVAC) system. Process history (supervised case) and a combination of clustering and deterministic techniques (semi-supervised case) are used to get the ground truth. This work differs from other research in that it derives the ground truth in the semi-supervised scenario and compares it extensively with sophisticated supervised models. Over 15 and 30 minutes, the best supervised model's Mean Absolute Error (MAE) was 0.032 and 0.034, respectively. The top semi-supervised model had an 86% Balanced Accuracy Score (BAS). A high - dimensional energy consumptions anomaly detection method based on deep learning was proposed by

[34]. The method uses high-dimensional energy consumption related data for both anomaly detection and real-time electricity consumption prediction. Test findings on a publicly accessible dataset demonstrate that the approach is capable of accurately identifying customers' unusual electricity usage patterns. Based on the data, building managers can discover irregular electricity usage by customers by implementing a real-time anomaly detection system in buildings. Users can also use the system to reduce energy waste and understand how much electricity they are using. The works on machine learning (ml) schemes for anomaly detection in solar power plants [35] make use of ML models to detect anomalies in photovoltaic. The Auto Encoder Long Short-Term Memory (AE-LSTM), Facebook-Prophet, and Isolation Forest techniques are assessed. These models are able to distinguish between the normal and aberrant responses of the PV system. The findings offer unambiguous information to help with decision-making, particularly when dealing with experimental trade-offs for a solution space this complicated.

### 3. System Model and Framework

The CRISP-DM methodology was employed for this study because it provides a structured framework for data-driven projects, ensuring a clear path from understanding the problem to delivering actionable recommendations. The six phases of CRISP-DM., business understanding, data understanding, data preparation, modeling, evaluation, and deployment, align closely with this project's objectives. The AI-driven anomaly detection system was implemented in Python to detect overheating in devices using a USB temperature sensor. The model was trained on temperature data as the model showed steady convergence, with training and validation loss decreasing over epochs.



**Figure 1.** Training vs Validation Loss.

#### 4. Result Discussion and Performance Evaluation

##### Evaluation Metrics

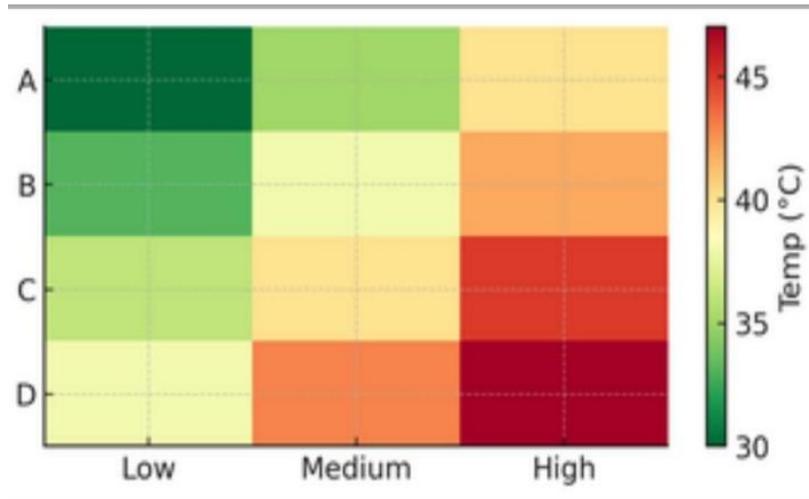
Accuracy: Proportion of correctly identified anomalies.

Precision and Recall: Trade-off between false positives and false negatives.

F1-Score: Balancing precision and recall.

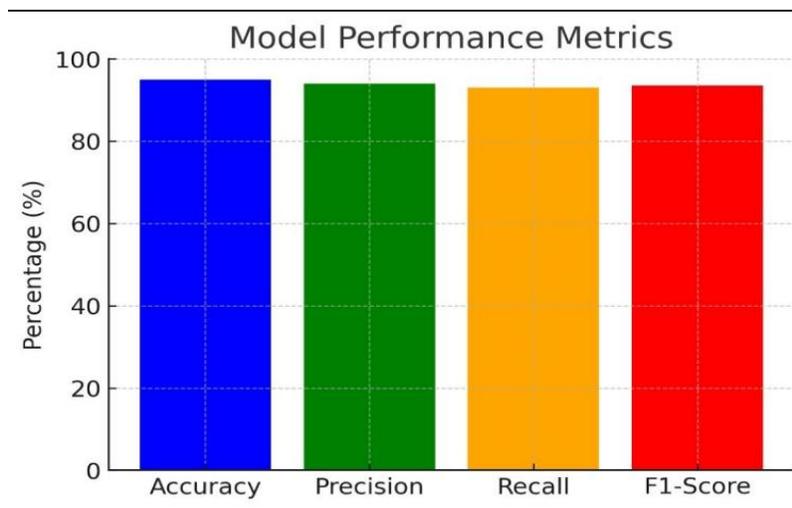
ROC-AUC: Overall measure of the model's classification performance.

The model achieved high accuracy in classifying normal and anomalous temperatures.



**Figure 2.** Heat map of the temperatures.

Metrics: Accuracy (95%), Precision (94%), Recall (93%), F1-Score (93.5%).



**Figure 3.** Model performance metrics.

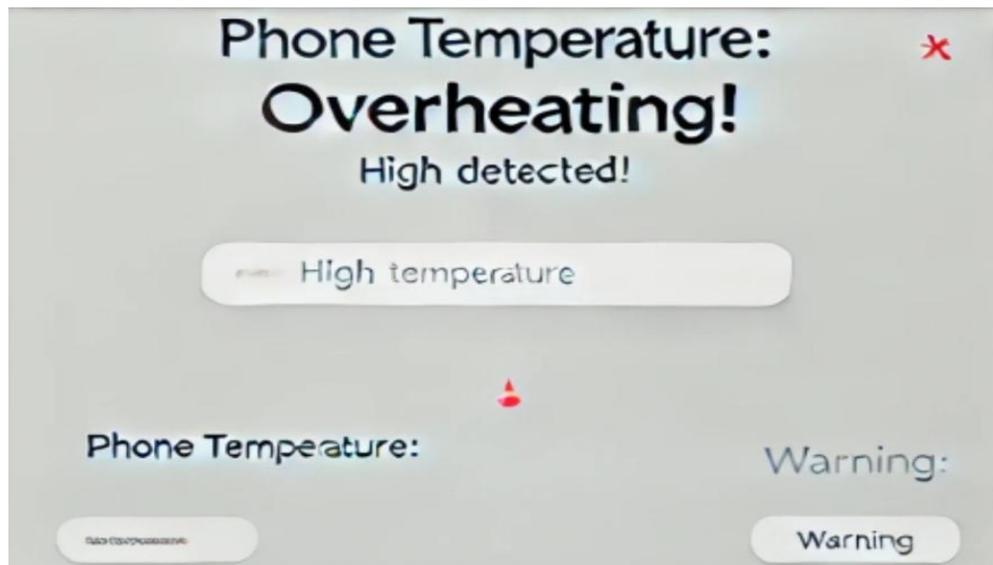
**Real-Time Detection:**

Normal Operation: The interface displays stable temperature readings, with a green indicator and no alerts.



**Figure 4.** Interface when phone temperature is normal.

Overheating Detected: The interface shows a temperature spike, a red indicator, and logs an alert.



**Figure 5.** Interface when phone temperature is overheating.



**Figure 6.** Interface of the GPU performance display.

## 5. Conclusions

This paper proposes a dynamic anomaly detection in energy systems. AI offers a smarter solution by analyzing energy usage in real-time and automatically spotting unusual patterns, such as a machine using more power than it should. This study shows that AI can help manage energy better by detecting wasteful usage and faults early. Instead of relying on manual inspections, AI can monitor energy use 24/7, making it more efficient and reliable. Although AI is highly effective, there are some challenges, such as ensuring data privacy, managing large amounts of data, and making AI systems easy to use. However, with continued improvements, AI-driven energy monitoring can become a standard solution for saving energy in buildings worldwide.

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