

ENERGY DEMAND PREDICTION AND THEFT DETECTION USING MACHINE LEARNING

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ABSTRACT

The project's main focus is on the thorough management of energy resources using demand forecasting, theft detection, and real-time monitoring. It uses voltage and AC current sensors to track energy usage; the collected data is timestamped and stored in a dataset. To overcome this difficulty, the use of Machine Learning (ML) methods into energy management systems has shown promise. Long Short-Term Memory (LSTM) neural networks are used to estimate the future energy consumption, which improves resource planning. Furthermore, a Support Vector Machine (SVM) algorithm trained on historical data is used to detect theft. The integration of these technologies is expected to transform the energy industry by promoting energy conservation, enabling proactive decision-making, and reducing financial losses brought on by energy theft. The collected data is safely uploaded to the ThingSpeak cloud platform, guaranteeing data accessibility and integrity. A web application is created to visualize energy usage, demand projections, and theft alarms in order to improve user involvement and control. In addition to addressing the urgent need for effective energy management, this initiative will help users fight energy theft, make educated decisions, and promote sustainability and resource conservation.

Keyword: Support vector machine (SVM), Long Short-Term Memory Algorithm (LSTM), Machine Learning techniques (ML). Internet of Things (IoT).

1. INTRODUCTION

Due to the increasing reliance of today's power system on renewable energy resources (RES), energy forecasting has become a major concern. Decision-makers and grid operators need to know how much power renewable energy sources (RES) will produce in the following days and hours. Furthermore, forecasting load demand and consumption is critical to the management and planning of modern power systems. Electrical energy storage is needed when there is reduced demand for power and excess power generation from the RES. However, due to energy storage's high cost, need for constant maintenance, and short lifespan, it cannot be stored in a significant amount. Because of this, utilities have to continuously balance supply and demand.

These limitations lead to a number of fascinating aspects of energy forecasting, including the need for absolute precision and data collection. Forecasting mistakes lead to a mismatch between supply and

demand, which is bad for operational expenses, reliability, and efficiency.

Data-driven models that leverage past electrical output data are reasonable choices. In this study, we employ data pre-processing methods to assess the performance accuracy of the data-driven forecasting model using historical power data that is readily available. The goal is to identify an appropriate anomaly detection technology and data-driven approach for energy production forecasting, as well as to develop a unified model for long-term forecasting with a step of short-term (hourly) precision.

There is a growing public concern about the sustainable use of energy resources. As a result of industrialization and population increase, energy management has become increasingly important. The project's objective is to create an improved system for energy monitoring, demand forecasting, and theft detection in order to address these issues in this particular context. Customers will be able to identify theft or irregularities early on, make educated decisions about their energy use, and obtain real-time insights into energy consumption with the aid of this comprehensive method.

1.1 Objectives

The primary objective of the Energy Demand Forecasting and Theft Detection using Machine Learning project is to enhance the efficiency, reliability, and security of the energy distribution system. This involves predicting future energy demand accurately and detecting instances of unauthorized energy consumption or theft.

1.2 Problem Identification

The ineffective management of energy resources is the main issue that this initiative aims to solve. Suboptimal resource allocation results from the frequent lack of precision and real-time insights in traditional techniques of monitoring energy consumption. Furthermore, energy theft is a serious problem that causes unequal resource distribution and huge revenue losses for energy providers. These issues are made worse by the deficiency of trustworthy theft detection systems. This project uses data analytics and cutting-edge technology to address these issues by enabling accurate demand prediction, proactive theft detection, and exact energy monitoring.

1.3 Outcome

It gives energy suppliers access to real-time data on energy usage, empowering them to allocate resources based on data. Second, by including demand prediction, energy is produced and delivered more effectively, resulting in less waste. Third, resource conservation and income protection are aided by theft detection. Users may easily access, monitor, and regulate energy management with the use of the online application and cloud-based data storage, which increases accountability and transparency. In the end, the initiative serves the interests of providers and customers while encouraging sustainability and responsible energy usage, providing a comprehensive response to the urgent problems of energy resource management.

1.3.1 PERFORMANCE METRICS

The following metrics are included in our model's performance evaluation:

- True Positive (TP): Cases where the theft is appropriately classified as such by the model.
- False Positive for (FP): Situations in where there is no stealing, but the model mistakenly

diagnoses the person as having PCOS.

- True Negative (TN): Situations in which the model correctly categorises cases as non-theft even though the theft is clearly not done.
- False Negative (FN): Situations in which theft occurs but are mistakenly classified as non-theft by the model.

1.3.1 ACCURACY

Accuracy serves as a crucial metric indicating the effectiveness of a model or algorithm in training and performance evaluation. In the context of this thesis, accuracy gauges the model's proficiency in detecting theft.

1.3.2 PRECISION

Precision represents the proportion of positively predicted cases that are truly positive. In the context of this thesis, precision quantifies the fraction of objects identified as theft

Recall, in essence, captures the ratio of actual positive cases correctly identified as positive by the model. In the context of this thesis, recall quantifies the fraction of follicles predicted as theft among instances

1.3.4 TRAINING TIME

Training time is crucially assessed to measure the duration necessary for training selected machine learning algorithms on the dataset.

1.3.5 F1 SCORE

The F1 score serves as a comprehensive metric blending precision and recall, reflecting the model's accuracy in identifying ovarian cysts within TV ultrasound images. A high F1 score suggests minimal false positives and false negatives, indicating the model's proficiency.

1.3.6 LOSS FUNCTION

Additionally, the loss function plays a pivotal role in aligning the ground truth with the output of the segmentation network. It aids in optimizing network weights based on features extracted across various resolutions, rather than solely focusing on individual pixel-level details.

2. OBJECTIVES OF THE PROPOSED WORK

The following goals will be accomplished by the project by utilising machine learning techniques:

1. **Accurate Demand Forecasting:** To accurately forecast energy demand, create and apply machine learning algorithms. The system's goal is to produce accurate projections for future energy needs by examining past consumption trends. Utility companies benefit from this by having better overall grid management.
2. **Load Balancing:** By predicting times of peak demand, you can enable proactive load balancing. The technology can assist utilities in distributing loads fairly, avoiding overloads, and lowering the chance of system failures by precisely predicting energy demand. This makes the infrastructure for distributing electricity more resilient and stable.

3. Promote effective resource allocation and management by offering information on the times and locations of expected peak energy consumption. This saves money and improves the environment by enabling energy suppliers to deploy resources—like power plants and distribution infrastructure.
4. Use machine learning techniques to look for odd patterns that might point to unapproved use or energy theft. The project intends to promote fair and equitable distribution of resources and minimise revenue losses for energy providers by swiftly recognising and resolving these situations.
5. Grid Security: Preventatively handle possible problems like overloads and system breakdowns to strengthen the security of the energy grid. Reducing the risk, accurate forecasting and theft detection enhance the energy infrastructure's overall resilience.

2.1.MATLAB SIMULINK

MATLAB Simulink is a powerful simulation and modelling environment. Simulink is a graphical programming environment that allows you to create and simulate dynamic systems using blocks and connections. Simulink excels in modelling dynamic systems, control systems, signal processing, and more, allowing users to represent physical components and their interactions using a visual representation of interconnected blocks.

2.2 Thingspeak Integration

ThingSpeak is a widely used Internet of Things (IoT) platform that provides cloud-based services for collecting, storing, and analysing data from connected devices. In this project, ThingSpeak serves as the cloud infrastructure for securely storing the energy consumption data and enabling data visualization.

2.3 LSTM for demand prediction

Long Short-Term Memory (LSTM) neural networks are employed for demand prediction in this project. LSTMs are a type of recurrent neural network (RNN) that are particularly well-suited for time series data.

2.4 SVM for Theft detection

Support Vector Machine (SVM) is used as the machine learning algorithm for theft detection. SVM is a supervised learning model that classifies data points into different categories based on their features [5]. In this project, SVM is applied to classify energy usage patterns as either normal or indicative of theft. The SVM-based theft detection process

3. PROPOSED WORK MODULES

The following actions are suggested for putting the Energy Management System with machine learning-based demand forecasting and theft detection into practice:

1. Real-time observation using AC sensors
2. Uploading data to the cloud platform ThingSpeak
3. Compiling and Timestamping Data
4. Using Machine Learning (ML) Approaches
5. Utilising LSTM Neural Networks for Demand Prediction
6. Using SVM for Theft detection

3.1MODULE DESCRIPTION:

3.1.1 DEMAND PREDICTION

Demand forecasting is a crucial part of the undertaking. Optimising energy generation, distribution, and utilisation requires accurate demand forecasts. The research makes use of recurrent neural networks (RNNs), specifically Long Short-Term Memory (LSTM) neural networks, to assess past data on energy consumption and forecast future need. Utilising LSTM models—which work well with time series data—the system can give consumers insightful information about when and how much energy is probably going to be needed. Energy suppliers can use this information to better allocate resources.

3.1.2 ENERGY THEFT DETECTION

Energy theft is a recurring issue in the energy sector, whether it is caused by illegal tactics such as metre manipulation. Energy providers experience significant income losses as a result of it, and there may even be safety risks. A Support Vector Machine (SVM) algorithm is integrated into the project to detect stealing. In order to find abnormalities or inconsistencies in real-time data, this algorithm is trained on previous patterns of energy usage. The system can send out notifications when it notices problematic patterns, enabling quick examination and action. The project promotes more sustainable energy distribution.

3.1.3 FEATURE EXTRACTION

During the initial processing stage, a range of techniques is applied to enhance the quality of theft detection. Model evaluation involves using various metrics and techniques to gauge how well a trained machine-learning model generalizes to new, unseen data. Common evaluation metrics include accuracy, precision, recall, F1 score, mean squared error, and many others, depending on the nature of the problem (classification, regression, etc.). Cross-validation is another technique used to assess a model's performance by splitting the dataset into multiple subsets for training and testing.

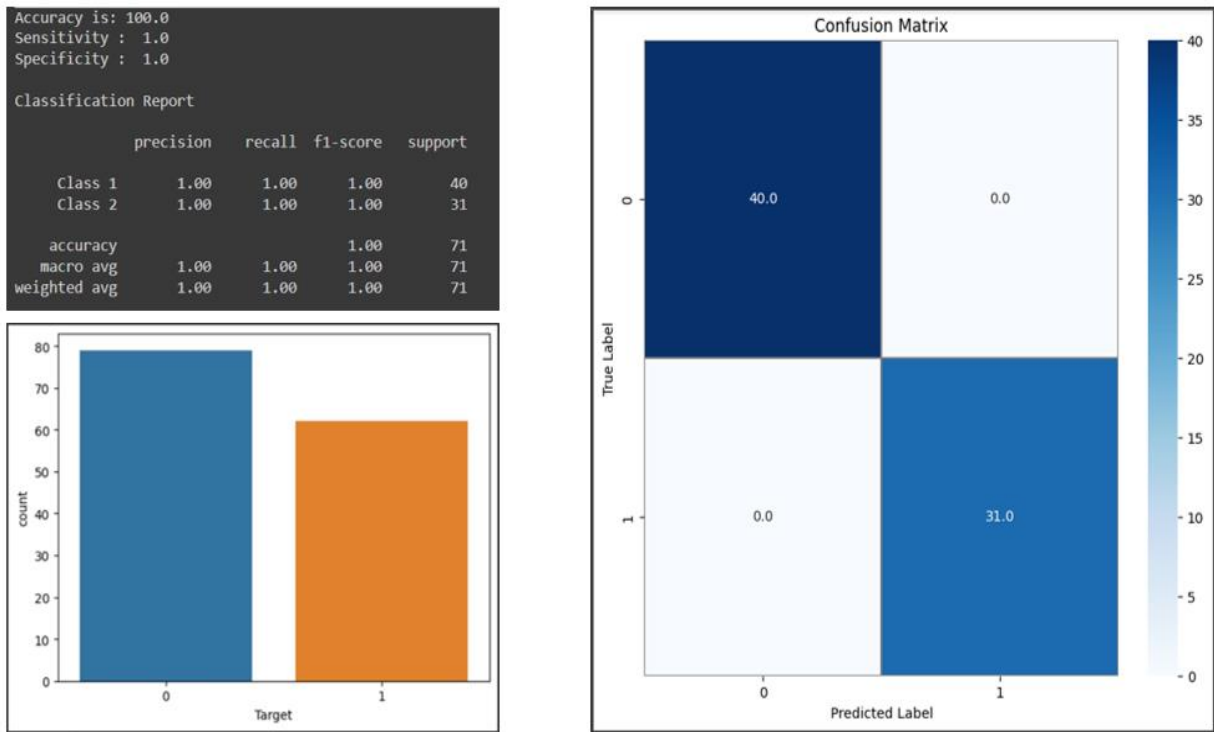


Fig 1- Theft detection

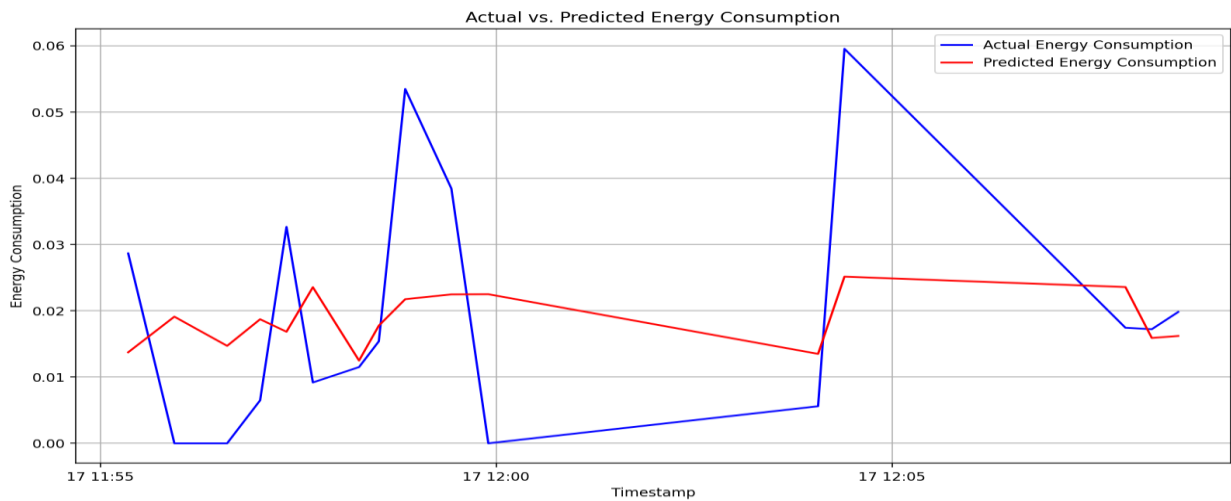


Fig 2-Actual vs Predicted energy

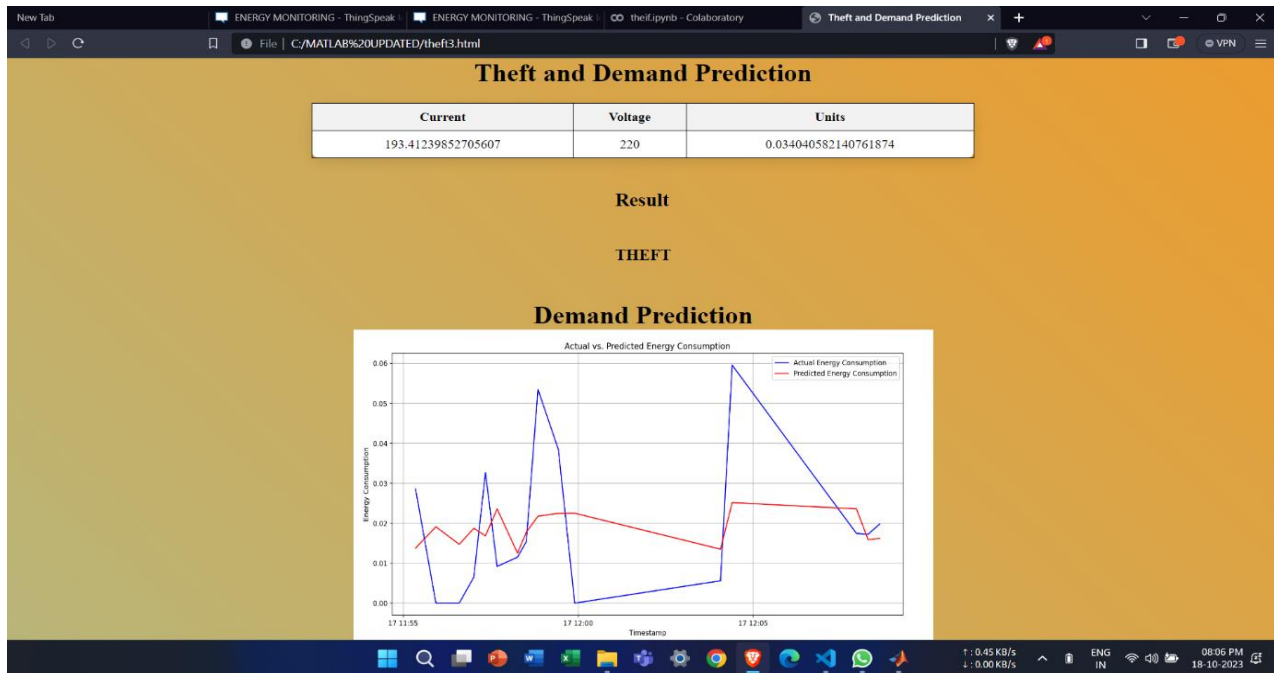


Fig 3-Website development for users

Use of confusion matrix

A confusion matrix is a performance evaluation tool commonly used in machine learning and classification tasks to assess the accuracy of a model. It provides a detailed breakdown of a model's predictions by comparing them to the actual classes of the data. The matrix is a square table where each row represents the instances in a predicted class, and each column represents the instances in an actual class. The main diagonal of the matrix represents correct predictions (true positives and true negatives), while off-diagonal elements represent misclassifications (false positives and false negatives). This visual representation helps to gain insights into the model's performance, highlighting where it excels and where it may need improvement. From the confusion matrix, various performance metrics such as accuracy, precision, recall, and F1 score can be derived, providing a comprehensive understanding of the model's effectiveness in handling different classes within the dataset.

4. CONCLUSIONS

The conclusion of this project offers an integrated system that successfully handles demand forecasting, theft detection, and real-time monitoring—all crucial components of energy management. It provides a comprehensive solution to the problems of energy resource optimisation and security, guaranteeing effective use of energy resources and protecting against unauthorised consumption by fusing physical components with cutting-edge data analytics techniques. In a world where energy consciousness is growing, this initiative is a useful tool for energy providers and consumers alike because of its contributions to sustainability, efficiency, and accountability.

5. REFERENCES

- [1] Nitin K Mucheli,Umakanta Nanda,D Nayak,P K Rout,S K Swain,S K Das,S M Biswal,"Smart Power Theft Detection System",2019 Devices for Integrated Circuit (DevIC)
- [2] Rohit Andore,S.S. Kulkarni,A. G Thosar,"Energy Meter and Power Theft Monitoring System",2023 IEEE International Students Conference on Electrical Electronics and Computer Science (SCEECS)
- [3] Sumit Mohanty,M. Mohamed Iqbal,Parvathy Thampi M.S.,"Controlling and Monitoring of Power Theft using Internet of Things",2021 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C)
- [4] Sanujit Sahoo,Daniel Nikovski,Toru Muso,Kaoru Tsuru,"Electricity theft detection using smart meter data",2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)
- [5] Taimur Shahzad Gill,Durr E Shehwar,Hira Memon,Sobia Khanam,Ali Ahmed,Urooj Shaukat,Abdul Mateen,Syed Sajjad Haider Zaidi,"IoT Based Smart Power Quality Monitoring and Electricity Theft Detection System",2021 16th International Conference on Emerging Technologies (ICET)

