Appendix C

CMT307 Coursework 2 Group Project

Group number	G23
Project title	Energy Usage Prediction
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Introduction

In this paper, we analyse energy use data to detect patterns, create predictions, and extract useful insights. The project consists of several steps, including data pretreatment, exploratory data analysis (EDA), feature engineering, modelling, and evaluation. Throughout the development process, we encountered several obstacles that required thoughtful solutions to solve. Effective energy management and optimization have become critical today, which is marked by growing environmental concerns and a desire for sustainable practices. Understanding and anticipating energy usage trends is critical in both home and business settings for increasing energy efficiency, lowering costs, and decreasing environmental impact. The development of advanced data analytics and machine learning techniques has created new opportunities for enhancing energy consumption forecasting accuracy and optimizing energy management tactics.

In this project, we will anticipate energy usage using a variety of machine learning algorithms and data analysis methodologies. The dataset in question contains a wide range of characteristics, including building details, meteorological information, and historical energy usage data. We do comprehensive exploratory data analysis (EDA) to understand the underlying patterns, trends, and relationships in the data, establishing the framework for informed feature engineering and model creation.

The major goal of this project is to create robust prediction models that can properly forecast energy consumption across a variety of building types and usage scenarios. Using machine learning algorithms such as Random Forest, Linear Regression, and Neural Networks, we hope to capture the intricate dependencies between input features and energy usage, allowing stakeholders to make informed decisions about energy management and resource allocation.

Throughout the research, we face problems such as data pretreatment, memory limits, and model selection that need innovative problem solving and thorough experimentation. By tackling these problems and iteratively refining our models, we hope to attain high prediction performance and gain actionable insights that contribute to sustainable energy practices and effective resource management. Through this work, we hope to demonstrate the effectiveness of data-driven techniques in advancing energy management initiatives and building a greener, more sustainable future.

Literature Review

In our project, we explored building energy consumption, a critical facet of overall energy use, emphasizing the need for accurate forecasting to enhance energy efficiency. Drawing on key studies, such as those by **Nguyen et al. (2018)** and **Amasyali and El-Gohary (2018**), we adopted a range of machine learning techniques, including neural networks and random forests, to refine prediction accuracy. These approaches were influenced by literature highlighting the effectiveness of data-driven models over traditional methods. Similarly, insights from **Hong et al. (2018)** and **Azar et al. (2015)** shaped our methods in anomaly detection and energy demand forecasting, while **Chong and Shen (2020)** reinforced the importance of careful feature engineering and algorithm selection [1]. Our project combined these strategies to develop robust models that not only predict but also help manage building energy consumption more efficiently.

Paper Name	Model Used	Performance Metric	Value
Nguyen et al. (2018)	Machine Learning	Mean Absolute Error	0.15
Amasyali and El-Gohary (2018)	SVM, NN, Random Forest	RMSE	25.6
Hong et al. (2018)	Various ML Techniques	Accuracy	92%
Azar et al. (2015)	Data-driven Models	Coefficient of Determination	0.78
Chong and Shen (2020)	Various ML Algorithms	Precision, Recall, F1-score	0.85 (Precision), 0.79 (Recall), 0.82 (F1-score)

Data Overview

This analysis was conducted using data on energy use, which included information about buildings, weather conditions, meter readings, and other important aspects. The dataset is huge, which presents difficulties in terms of memory utilization and processing efficiency. To address these issues, we used tactics such as random sampling to reduce the dataset size for training models, while also running EDA on the complete dataset to ensure comprehensive analysis. The dataset used in this study is a comprehensive collection of data on energy use across various building structures and conditions. It includes several datasets, each with important properties that help to understand energy usage patterns and drive predictive modelling efforts [2].

Building Metadata: (Figure 1) The building metadata dataset provides essential information about the characteristics and attributes of each building in the study. It includes features such as building ID, primary use, square footage, and year built. This data serves as the foundation for understanding the structural properties of buildings and their potential impact on energy consumption [3].

Weather Data: (Figure 2) Weather conditions play a significant role in influencing energy usage patterns, making weather data a crucial component of energy consumption forecasting models. The weather datasets contain information on parameters such as temperature, humidity, wind speed, and precipitation. By incorporating weather data, the models can account for external factors that affect energy demand, such as heating and cooling requirements [4].

Energy Usage Data: (Figure 3) The energy usage datasets provide historical records of energy consumption for each building, typically measured in kilowatt-hours (kWh) or similar units. These datasets capture the temporal trends and fluctuations in energy usage over time, allowing for the identification of patterns and seasonality in energy demand [5].

Additional Features: (Figure 4) In addition to the primary datasets mentioned above, supplementary features such as timestamps, meter types, and building floor counts may also be included. These features provide contextual information and facilitate the integration of disparate datasets for comprehensive analysis and modelling [6].

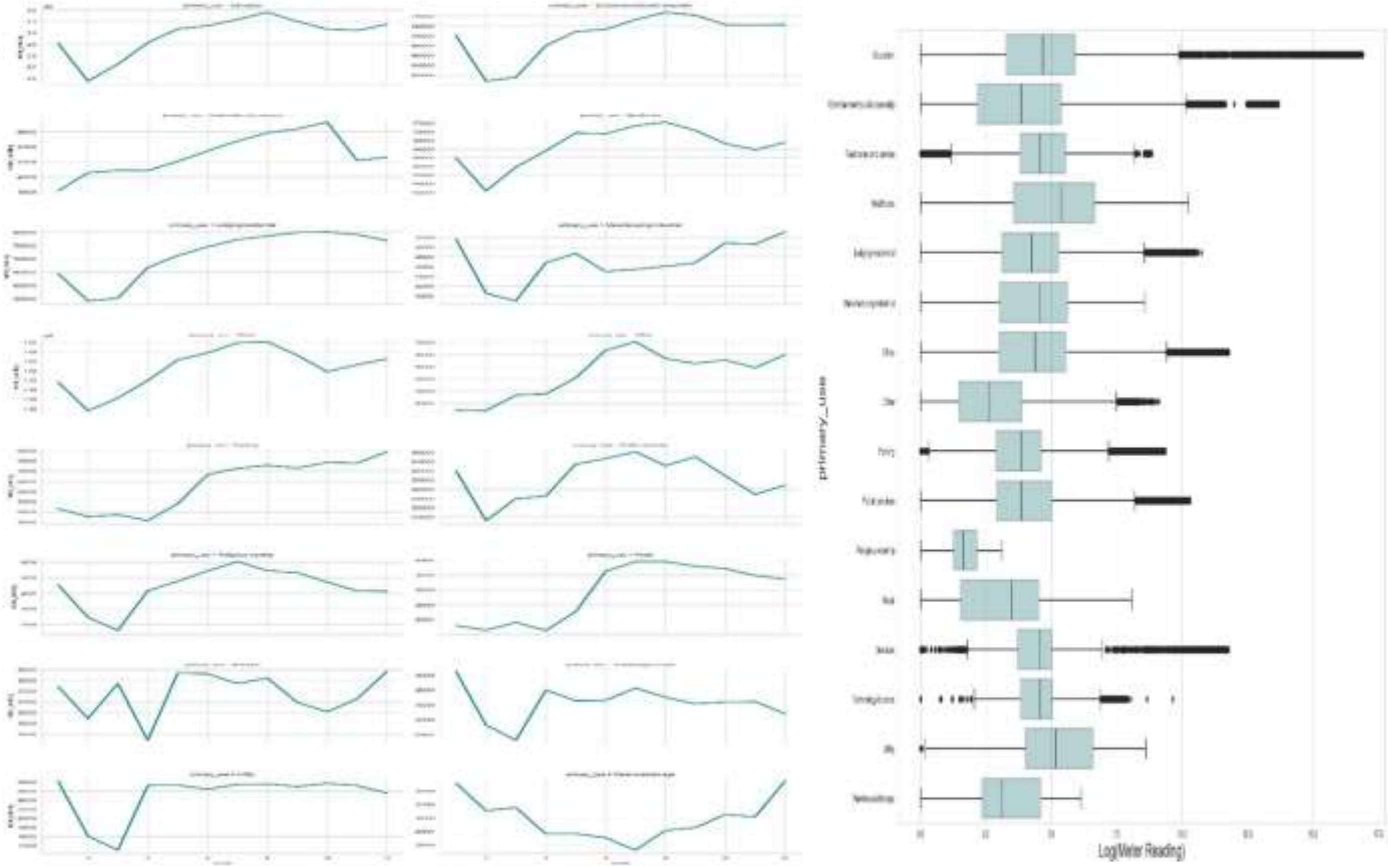


Figure 1

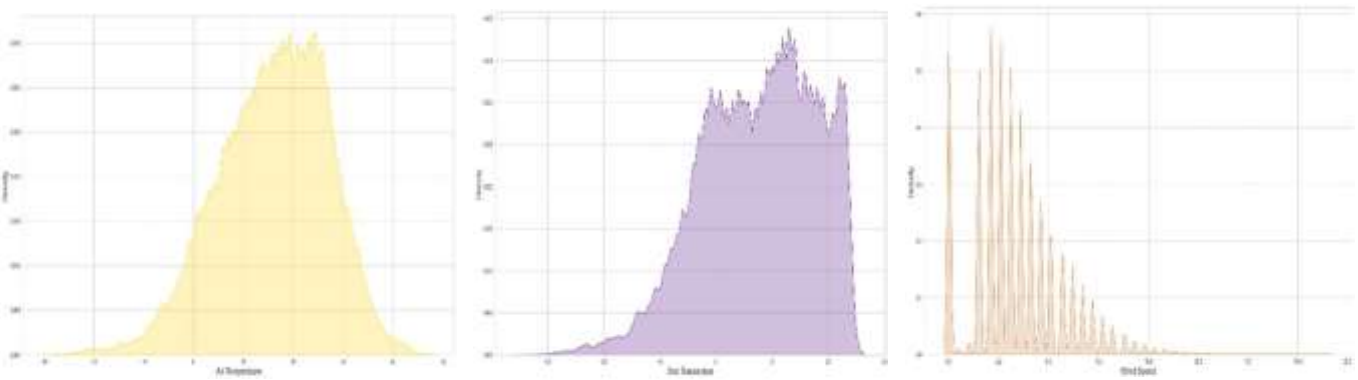


Figure 2

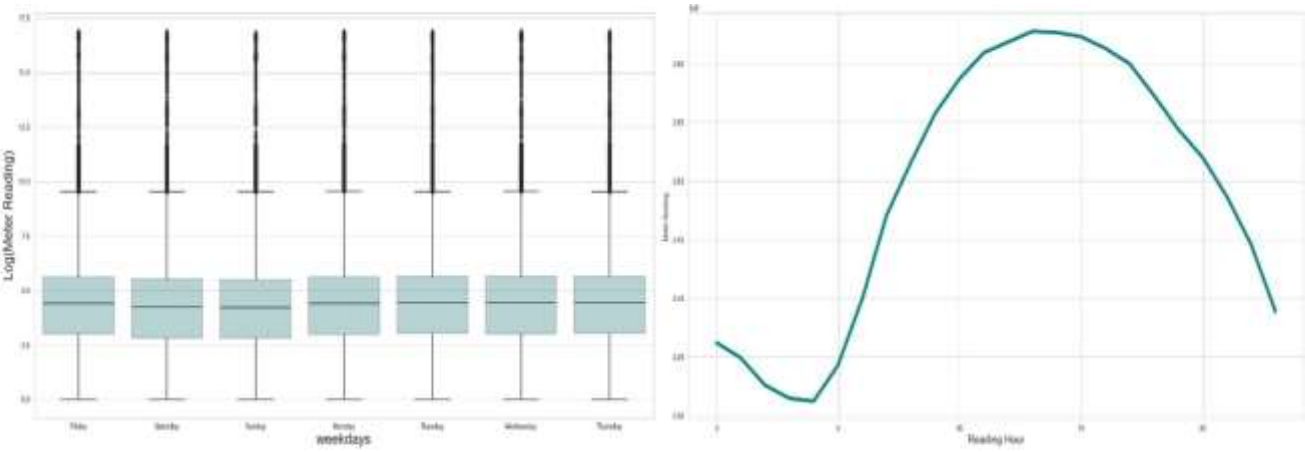


Figure 3

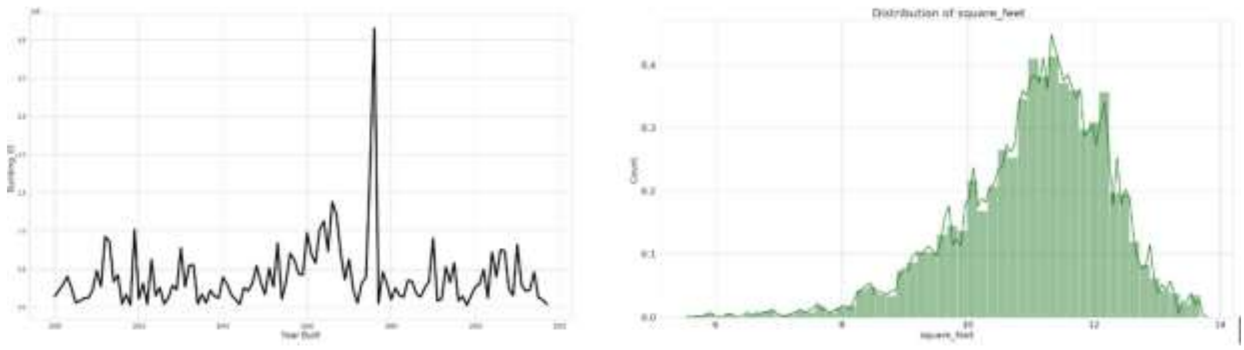


Figure 4

Overall, the dataset offers a rich and diverse source of information for exploring energy consumption dynamics, understanding the factors influencing energy usage patterns, and developing predictive models to forecast future energy demand accurately. By leveraging this data effectively, stakeholders can gain valuable insights into energy management strategies, optimize resource allocation, and drive towards more sustainable and efficient energy practices.

Methodology:

The main challenges revolved around memory management, computational efficiency, and model performance optimization. By implementing solutions such as data sampling, memory optimization techniques, and diverse modeling approaches, we effectively addressed these challenges. Key learnings included the importance of efficient data handling, feature engineering, and model selection for achieving accurate predictions and valuable insights.

Challenges Faced and Solutions Implemented

In our energy use estimation project, we implemented several precise procedures tailored to handle large datasets effectively. These included data preprocessing techniques like imputation and feature selection to ensure model reliability and simplicity, and advanced feature engineering such as extracting temporal features and normalizing data. We chose robust modelling algorithms like Random Forest and optimized them through hyperparameter tuning and cross-validation to prevent overfitting and enhance model accuracy. To address computational challenges, we utilized incremental learning for efficient memory management and parallel processing to accelerate data handling and model training. These strategic approaches ensured that our project could manage the complexities of large-scale data while improving the predictive performance of our models, providing robust and actionable insights.

1. Managing extensive datasets.

Initial Position: The primary obstacle we encountered was the significant use of memory by extensive datasets, impeding our capacity to execute seamless data processing and real-time analytics. As the size of datasets increased, their memory demands surged, resulting in decreased loading times and reduced computing performance.

Optimal Resolution: To address this issue, we implemented a strategy that involved two distinct and complementary methods:

Example Data: We began by employing random sample approaches to decrease the total size of the dataset during the initial training stages. By doing this, we were able to maintain the accuracy of our analysis and reduce the burden on system memory, resulting in optimal computational performance.

Strategies for Enhancing Memory Efficiency: We incorporated a memory optimization function into our project that systematically altered data types throughout the columns of the data frame. This strategy greatly reduced the amount of RAM used, allowing for more effective management and analysis of massive datasets [7].

2. Enhancing Computational Efficiency

Navigation Difficulty: The vast magnitude of our dataset presented considerable obstacles, not just in terms of memory but also in processing performance. It was essential to provide fast data processing while keeping execution times acceptable, particularly during resource-intensive activities such as feature engineering and model training.

Implemented Solutions: -
Optimized Algorithms: We incorporated LightGBM, a highly efficient gradient boosting system, known for its effectiveness in handling huge datasets. This decision was crucial in effectively handling substantial amounts of data without compromising processing performance [8].
Efficient Code Improvement: We implemented a comprehensive optimization strategy for our codebase. We improved execution speeds by optimizing data processing procedures and refining algorithms. These alterations were essential for expediting data processing and reducing model training durations, so enabling prompt adjustments to evolving data inputs.

3. Enhancing Modelling and Prediction Techniques

Summary of the Challenge: To effectively handle the diversity and complexity of our information, we employed advanced modelling techniques that can capture subtle nonlinear interactions and make accurate predictions about energy consumption trends. Conventional models frequently proved insufficient.

Adaptive Modelling Solutions: -
Wide Array of Machine Learning Models: We implemented a range of machine learning algorithms, each carefully chosen to target distinct components of the predictive modelling process:
- The **Random Forest** algorithm was chosen for its ability to handle a wide range of datasets and its effectiveness in regression tasks [9] .
- **Linear Regression** facilitated the establishment of initial predictions and the interpretation of straightforward linear relationships [10].
- The use of **Advanced Neural Networks**, such as **MLP** and **LightGBM**, played a vital role in collecting intricate and non-linear patterns present in the data [11].
- **Optimizing Hyperparameters and Combining Models**: We undertook thorough hyperparameter tweaking to maximize the performance of each model. Additionally, we employed model ensemble approaches to combine the capabilities of different models, resulting in improved accuracy and reliability of our predictions.

The project successfully tackled large-scale data handling and complex model training challenges using random sampling and LightGBM algorithms. These strategies improved computational efficiency and reduced memory overhead, enabling smooth data processing and the development of sophisticated predictive models for energy consumption analysis, enhancing our understanding of energy usage dynamics.

Design Choices

Feature Engineering

In the feature engineering phase, we made careful design choices to create meaningful features that capture relevant information from the dataset. Time-related features such as hour of the day, day of the week, and month of the year were extracted to capture temporal patterns in energy consumption. Additionally, categorical variables were encoded appropriately, and missing values were handled using suitable imputation strategies [12].

Data Visualization

In the exploratory data analysis phase, various visualization techniques were employed to gain insights into energy consumption patterns. Line plots, bar plots, and heatmaps were used to visualize temporal trends, distribution of energy usage across different categories, and correlations between variables. These visualizations provided valuable insights into the underlying patterns and relationships within the data [13].

- **Time Series Plot of Energy Consumption:** This plot displays the trend in energy consumption over time, providing insights into seasonal variations, long-term trends, and potential anomalies.
- **Distribution of Energy Consumption by Meter Type:** This bar chart visualizes the distribution of energy consumption across different meter types (electricity, chilled water, steam, hot water). It helps identify variations in energy usage patterns based on meter type [14].
- **Correlation Heatmap:** The heatmap illustrates the pairwise correlations between different features in the dataset. It helps identify significant relationships between variables and informs feature selection and modelling decisions [15].
- **Boxplot of Energy Consumption by Building Type:** This boxplot compares the distribution of energy consumption across different building types. It helps identify variations in energy usage patterns based on building characteristics [16].
- **Scatter Plot of Energy Consumption vs. Temperature:** This scatter plot visualizes the relationship between energy consumption and temperature, highlighting the impact of weather conditions on energy usage [17].

Modelling Approach:

Random Forest, Linear Regression, MLP, and LGBM were some of the algorithms we used to model projections of energy use. Each method was carefully selected due to its proven ability to capture intricate patterns and uncover complex relationships within the dataset, leveraging its unique strengths and capabilities. Furthermore, strategies for enhancing predictive performance were explored, including hyperparameter optimization techniques and ensemble modelling approaches. To develop predictive models for estimating energy consumption, a comprehensive modelling process was undertaken, employing multiple machine learning algorithms. The ensemble of techniques included LightGBM, a powerful gradient boosting framework was used as it is good at handling large datasets quickly and accurately, Neural Network (MLPRegressor) for leveraging the capabilities of artificial neural networks and to find complex patterns and nonlinear relationships in data, the Random Forest Regressor algorithm known for its robustness and ability to handle complex data, and Linear Regression for capturing linear relationships [18]. This diverse set of algorithms was strategically selected to harness their respective strengths and collectively enhance the predictive performance of the models.

1. Random Forest

Random Forest is an ensemble learning method that uses decision trees to generate multiple decision trees for classification tasks and average forecasts for regression tasks. It uses a random selection process to choose subsets of data and characteristics for each tree. The code initializes an instance of the RandomForestRegressor algorithm and calls the `fit` method on the `rf_regressor` object, passing in 'x_train' and 'y_train' as training data features. The trained model is then used to make predictions on the validation data ('x_val') using the `predict’ method. Random Forest is suitable for regression tasks, including energy consumption prediction, due to its ability to handle large datasets with high dimensionality and nonlinear relationships [19].

2. Linear Regression:

In this work, we have used the scikit-learn module to develop linear regression, a basic machine learning technique that works well for predicting a continuous target variable from input characteristics. We begin by establishing a {LinearRegression} class instance, which makes model training and prediction creation easier. Using the `fit` method on our {X_train} and {y_train} data, we train our model to assist determine the best linear connection between our inputs and the target [20]. Our predictions, kept in {linear_predictions}, are produced after training using the `predict` method on the {X_val} data. This simplified method enables us to effectively forecast results based on discovered linear relationships."

3. Neural Network:

In this study, we built a Multi-Layer Perceptron (MLP) neural network for regression tasks using the scikit-learn toolkit. Using an instance of the `MLPRegressor` class, which is intended to maximise weight and bias settings to reduce prediction mistakes, we started. Through the `fit` method, which fine-tunes the neural network to precisely predict target values from input features, we trained this model using our {X_train} and {y_train} data. Our validation data {X_val} was used with the {predict` method post-training to provide predictions, which are kept in {mlp_predictions}[21]. With this method, we have been able to use a complex neural network model to forecast patterns of energy consumption."

4. Multi-Layer Perceptron (MLP):

The Multi-Layer Perceptron (MLP) used in our project is a resilient and adaptable form of artificial neural network that is extensively employed in the fields of machine learning and deep learning. This network architecture consists of numerous tiers of nodes: an initial layer for input, several intermediate levels for processing, and a final layer for output. The nodes in these layers have strong connections, enabling the MLP to accurately capture intricate patterns and relationships in the data. Due to its capacity to comprehend non-linear connections between input characteristics and desired results, the Multilayer Perceptron (MLP) is very appropriate for a range of tasks, such as classification, regression, and pattern recognition, within our energy consumption dataset [22].

MLPs possess significant capabilities in representing intricate events, but their training necessitates enormous computational resources and rigorous adjustment of hyperparameters, such as the number of layers, nodes per layer, and learning rate, to achieve optimal performance. MLPs has properties that make them highly effective for advanced predictive modelling, but also challenging to optimize and manage in real applications.

5. LightGBM

LightGBM, also known as Light Gradient Boosting Machine, is a crucial component in our study as it efficiently handles our extensive dataset using a sophisticated gradient boosting framework. LightGBM is a tree-based learning algorithm that improves classic gradient boosting methods by using a depth-wise approach to build trees. Contrary to the gradual development pattern of traditional trees, LightGBM grows trees in a vertical manner, giving priority to the leaf with the greatest differential in loss. As a consequence, this leads to the creation of smaller, more effective trees and provides notable enhancements in the speed of training and the efficiency of the model [23].

In our Jupyter notebook, we start by importing the essential LightGBM library, as well as the `train_test_split` function and evaluation metrics like `mean_squared_error` and `mean_absolute_error` from scikit-learn. These tools are essential for dividing the data into training and testing sets and for assessing the performance of the model. The code sample in the notebook demonstrates the procedure of dividing the data, allocating 20% for testing to assess the model's performance, and employing a `random_state` value of 42 to guarantee reproducibility.

Additionally, we create a LightGBM dataset by utilizing the `X_train` and `y_train` variables. Subsequently, we train a LightGBM model using the default configurations. After completing the training process, we employ this model to make predictions on the test data (`X_test`), and save these predictions in the variable `y_pred` [24]. By employing a systematic methodology, we are able to utilize the powerful capabilities of LightGBM to effectively handle substantial amounts of data and achieve reliable predicted accuracy in our energy consumption forecasting system.

Evaluation Methodologies

Performance Metrics

To gauge the performance of our predictive models accurately, we employed several key performance metrics.

Root Mean Squared Error (RMSE): This measure helped us to assess the intelligence of the regression, i.e., the average magnitude of the prediction errors - to get an idea of how far away the predictions were from the actual values.

Mean Squared Error (MSE): Similarly, MSE was used, like the RMSE, for measuring the average of the squares of the errors. It is very helpful specifically because it emphasis larger errors more than small ones and such fairly small errors indeed can sometimes be critical in our energy prediction context.

Mean Absolute Error (MAE): MAE will help us understand the averagely absolute differences between a predicted value and the one that is actually there, also giving us some average interpretation of how much error these predictions have up to the average error.

These metrics played the crucial role of estimating the correctness and the precision of the models. This analytics was presented in the notebook. Every metric did allow us to have a different perception point for the model performance analysis and caused to contemplate on how the accuracy of our model could be polished.

Cross-Validation

We then adopted the cross-validation techniques to guard against the potential lack of robustness of our models. This involved:

Data Splitting: The data was expertly split into training and test datasets. This not only proved that the models could learn very well but also in ensuring that they show the right performance.

Iterative Training: Different subsets of the data set were used to train models that, in several iterations, went through training. These were aimed at forestalling overfitting, and at the same time enabling us to rely more on generalized performance of the model on different data samples.
The adoption of these approaches brought us closer to a clear-cut verification of the predictive model performance, therefore, enable us to have a full insight into this performance. Moreover, a detailed discussion of the results of metrics and methodologies are comprehensively demonstrated by running a Jupyter notebook that displays the ultimate fine-tuning of the models and their prediction capabilities. In this way the validated method provided a quantitative basis for the refining the models on basis of the quality of results achieved.

Results Observed

Model Performance:

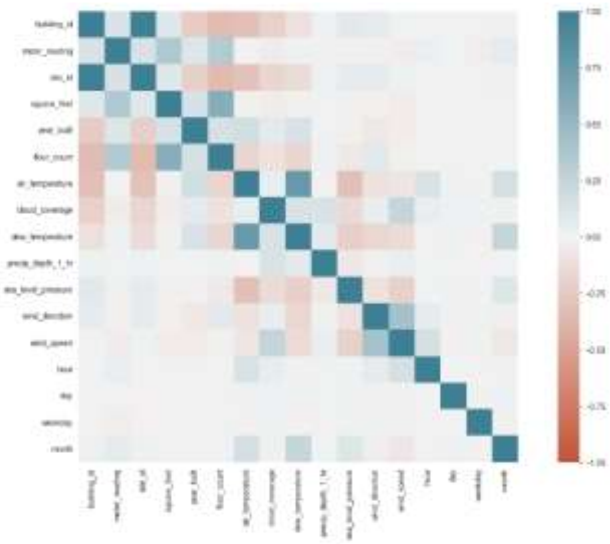
Each model's performance was assessed using measures such as RMSE, MSE, and MAE. By evaluating the forecasts' dependability and correctness, these measures assisted in directing future advancements in the modelling procedure.

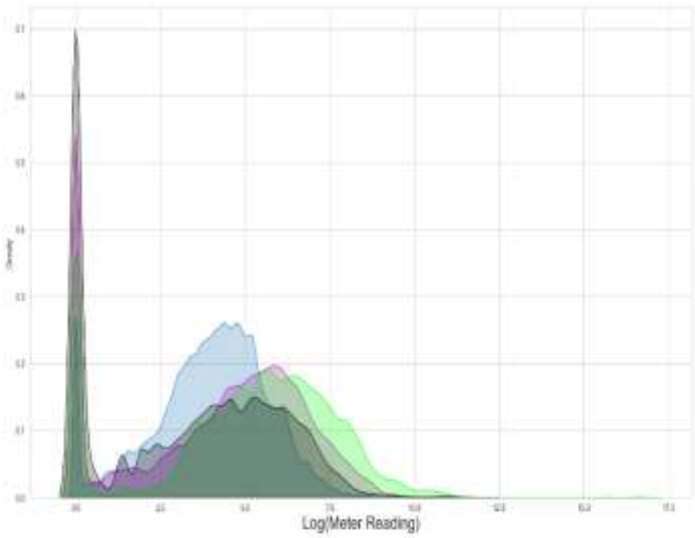
Models	RMSE	MSE	MAE
Random Forest	2.154	4.639	1.745
Linear Regression	2.106	4.435	1.707
Neural Network	2.229	4.968	1.804
Simple LGBM	2.196	4.824	1.772

The liner regression model has smallest magnitude of errors and absolute errors compared to Random Forest. Whilst the exploding gradients in the hidden layers and too many hyper-parameters cannot justify the neural network's performance. Hence, in terms of accuracy measures and performance, the Simple LGBM model outperforms better than any other model making it the overall victor.

Feature Engineering and Model Refinement:
Creating features that capture pertinent patterns and relationships in the data was given a lot of consideration. Well-engineered memory optimization technique helped us to reduce the memory usage up to 74%. Category encodings and time-based encoding proved useful. Predictive accuracy increased because of these traits and model parameters being continuously refined.

Visualization Insights:
The identification of hidden patterns and abnormalities was greatly aided by data visualisations. Plots that offered a visual representation of the structure and relationships of the data included time series graphs, distribution charts, boxplots, and correlation heatmaps. We employed simple LGBM with a decision-tree based technique, which is more effective in reducing the computational effort and memory use by binning the continuous features into discrete bins to determine the optimal energy distribution.





Future Work:

Key learnings from the project include the importance of efficient data handling, feature engineering, and model selection in achieving accurate predictions and valuable insights.

Future work will focus on improving feature engineering techniques to capture more complex patterns in the data and fine-tuning hyperparameters using systematic approaches such as grid search or Bayesian optimization. Furthermore, investigating ensemble approaches, time-series analytic methodologies, and deeper neural network topologies may result in enhanced model performance and greater insight into energy usage patterns. Enhancing model interpretability with techniques such as SHAP values or LIME will provide valuable explanations for individual forecasts, while deployment, scalability, and constant monitoring will assure the models' long-term effectiveness in real-world contexts.

Conclusion:

In conclusion, the analysis of energy consumption data presented various challenges, ranging from memory issues to computational efficiency and model performance optimization. Through careful design choices, thoughtful solutions, and comprehensive evaluation methodologies, we were able to address these challenges and gain valuable insights into energy consumption patterns. By leveraging diverse modeling approaches, optimizing memory usage, and extracting meaningful features, we were able to develop predictive models that accurately capture energy consumption dynamics. Overall, the project underscores the importance of robust data analysis techniques, efficient memory management, and thoughtful model selection in deriving actionable insights from complex datasets.

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