



Energy Consumption Forecasting

Using Deep Learning Models

Capstone Project by
Divij Arora





Problem Statement

- Forecast household electricity consumption on an hourly basis using historical energy usage data.
- The goal is to predict the 'Global_active_power' consumption value for the next hour based on the previous 24 hours of readings.



Stakeholders

&

Business Use Case

- Utility Providers: Load balancing and demand forecasting
- Consumers: Optimize energy usage
- Smart Grid Systems: Enable automation and anomaly detection



Approach

Data Preparation

1. Load the Dataset.
2. Combine and Format Datetime
3. Resample the Data
4. Handle Missing Values
5. Select Features and Scale.
6. Create Time Series Sequences

Train Model

1. Train LSTM Model
2. Train GRU Model
3. Train XGBoost Model

Model Evaluation

1. Predict Using Test Data
2. Inverse Transform
3. Calculate Metrics like MAE, MSE, R^2
4. Visualize Results

Model

Summary



Data points	Original dataset -2075259 After resampling - 34589 Test dataset - 27652 Train dataset - 6913
Data preparations	1. Resample Hourly 2. Handle missing values
Preprocessing	1. Minmax scaling 2. Create sequence
Models used	LTSM GRU XGBoost
Metrics used	Mean Absolute error Mean Square error R2

Model

Summary

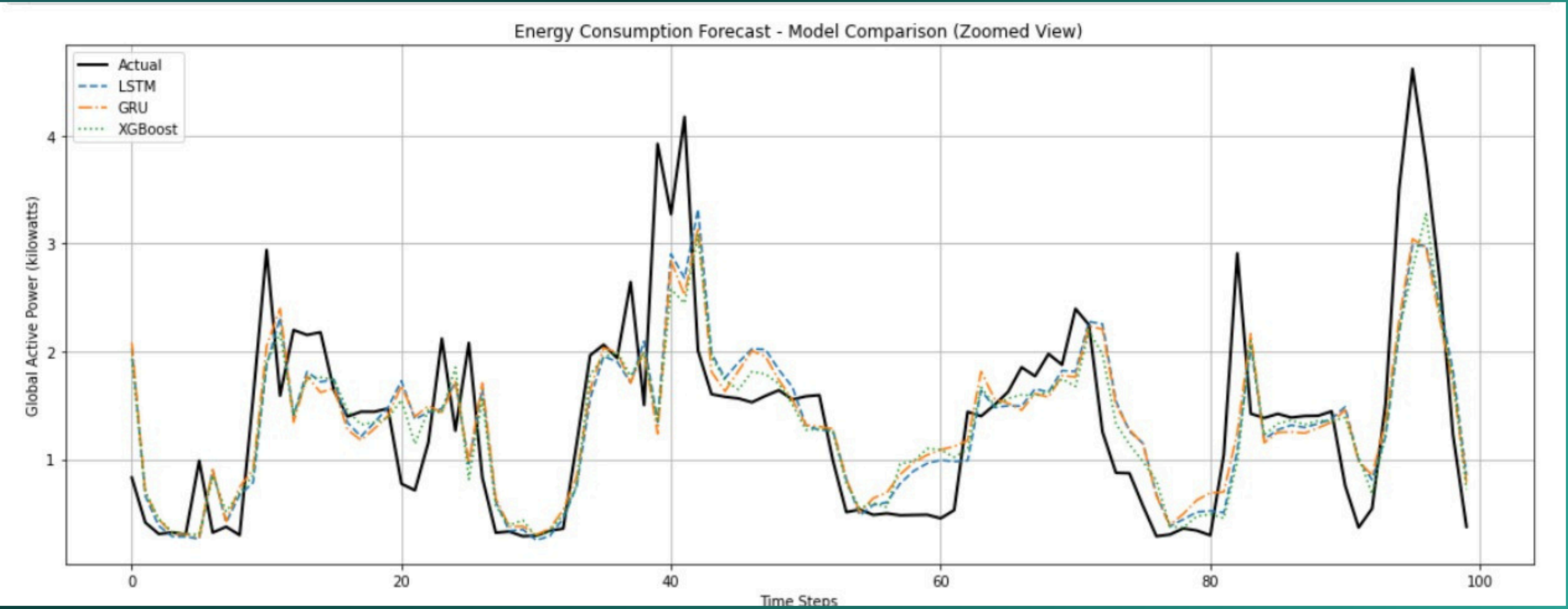


Model	Parameters
LSTM	LSTM layer - 64 neurons Dropout layer - drops 20% Dense Layer - 1 neuron Optimizer - Adam optimizer Loss function - Mean Squared Error (MSE) Epoch = 20 Batch size = 32
GRU	GRU layer - 64 neurons Dropout layer - drops 20% Dense Layer - 1 neuron Optimizer - Adam optimizer Loss function - Mean Squared Error (MSE) Epoch = 20 Batch size = 32
XGBoost	Number of Trees (Estimators) - Default is 100 Loss Function - Mean Squared Error (MSE) Optimization - Gradient boosting



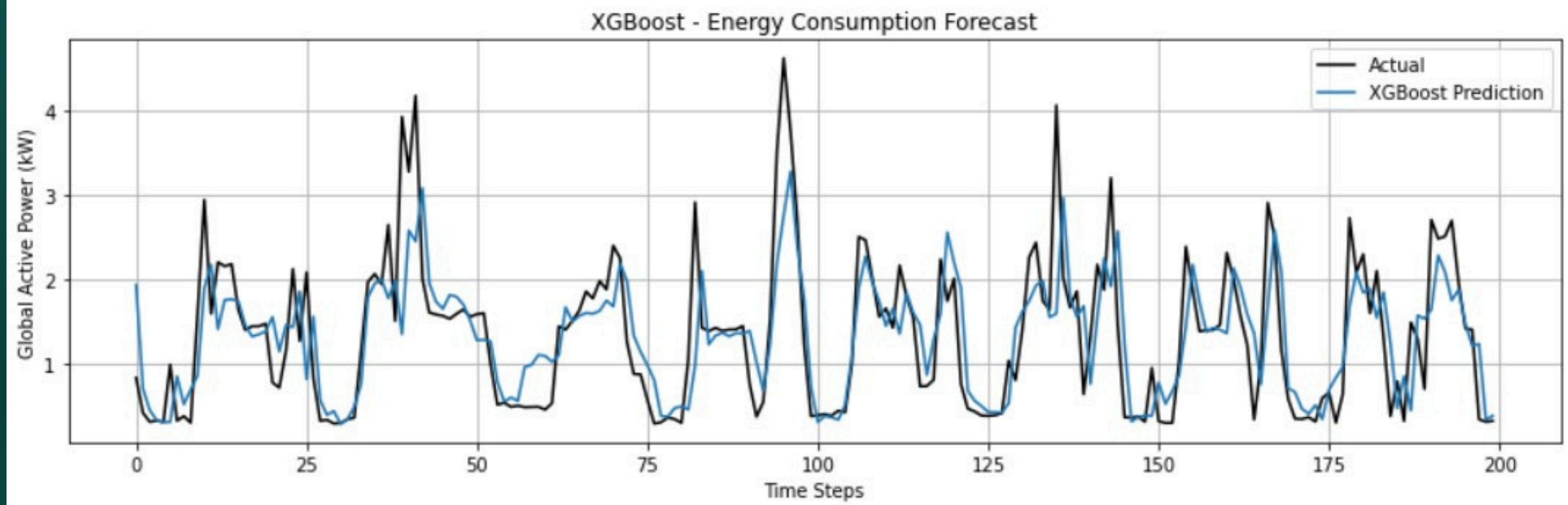
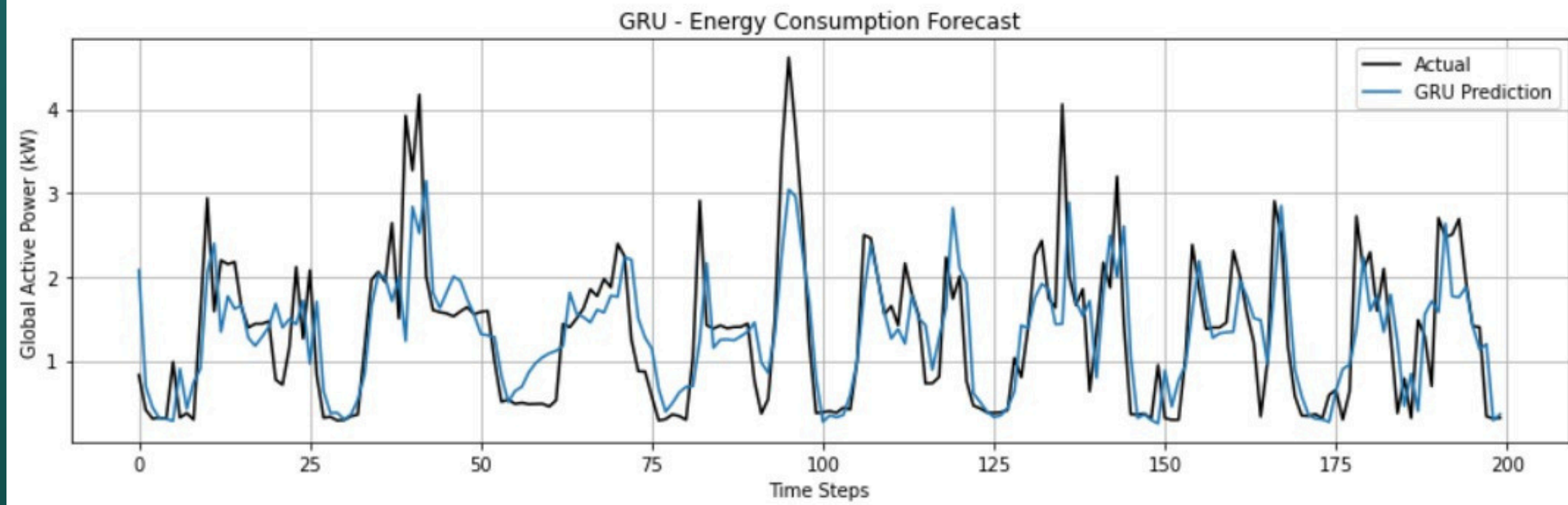
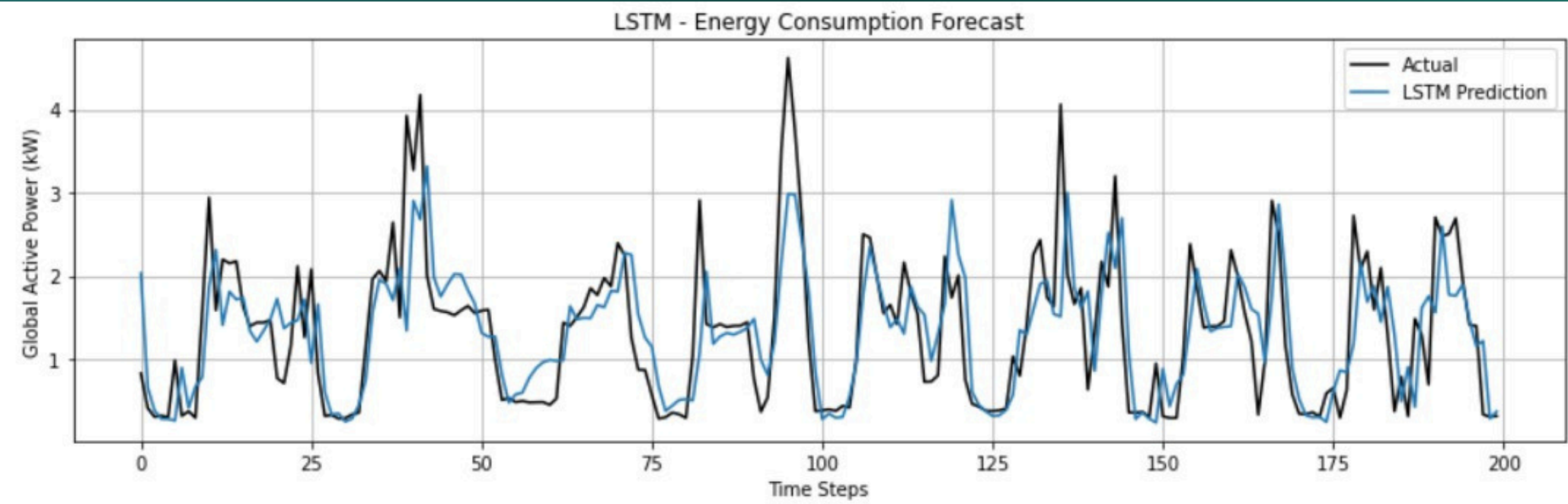
Results

MODEL	MAE	MSE	R2
LSTM	0.35	0.25	0.52
GRU	0.36	0.26	0.52
XGBoost	0.35	0.25	0.53





Results





Inferences

1. XGBoost Outperforms Deep Learning Models
 - a. Achieved the highest R^2 score (0.53), showing it captured slightly more variance in the data.
 - b. Also matched LSTM in MAE and MSE.
2. LSTM slightly edges out GRU with lower error values (MAE: 0.35 vs 0.36).
3. All models achieved moderate R^2 (~ 0.52 – 0.53), indicating there's room to improve predictive power with additional features.



References

&

Comments

- Code Link – https://github.com/Divi95/AI_ML_Submissions/tree/main/AI-ML%20Project
- Dataset source: <https://www.kaggle.com/datasets/uciml/electric-power-consumption-data-set>
- <https://medium.com/nerd-for-tech/how-to-prepare-time-series-data-for-lstm-rnn-data-windowing-8d44b63a29d5>
- Hands-On Machine Learning with Scikit-Learn, Keras, and Tensorflow – Aurelien Geron

- Add External Features
 - Enhance forecasting accuracy by incorporating: Weather data (temperature, humidity)
- Explore Transformer Models
 - Implement Temporal Fusion Transformers (TFT) or Informer/Transformer models.
- Anomaly Detection Integration
 - Add an anomaly detection pipeline to identify unusual spikes (possible theft or malfunction).