Attention-Aware Deep Learning Framework for Smart Home Energy Forecasting

MSc Research Project

Programme Name: MSc in Data Analytics

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MSc Project Submission Sheet

School of Computing

Student Name: ……. Harishwar…Yadav…Elgamoni……
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Programme: ……MSc…Data Analytics…… **Year:** ……2024-2025…….
Module: ……(Research) Practicum……

Lecturer: ……14-08-2025…….……
Submission Due Date: ……

Project Title: ……. Attention-Aware Deep Learning Framework for Smart Home Energy Forecasting

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Attention-Aware Deep Learning Framework for Smart Home Energy Forecasting

Name: Harishwar Yadav

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System Infrastructure Requirements

- **Operating System Compatibility**
    - **Preferred Environment**: Windows 10 or Windows 11 — offers the widest support for development tools and integrated libraries
    - **Alternative Environment**: Ubuntu 20.04 LTS or newer — ideal for opensource development and server-based configurations
- **Processor Specifications**
    - **Minimum**: Multi-core CPU (Intel Core i5 / AMD Ryzen 5 or newer) for basic operations
    - **Recommended**: Quad-core or higher for faster processing, model training, and parallel task execution
- **Memory Requirements**
    - **Minimum**: 16 GB RAM — suitable for standard testing and moderate data handling
    - **Optimal**: 32 GB RAM or more to efficiently process large datasets and run simultaneous experiments
- **Enhanced Performance Option**
    - NVIDIA GPU with CUDA support — enables significantly faster deep learning computations and training processes
- **Storage Capacity**
    - 15–20 GB of available disk space for datasets (raw and processed), model

checkpoints, embeddings, visualization files, and required libraries

Software Setup Guidelines

- **Programming Language**
    - Python 3.9 or later — recommended for best compatibility with modern libraries
- **Key Data Analysis Libraries**
    - pandas — for structured data handling and transformation *(pip install pandas)*
    - numpy — for numerical calculations and array-based processing *(pip install numpy)*
    - matplotlib — for generating static charts and visual outputs *(pip install matplotlib)*
    - seaborn — for advanced and statistical visualizations *(pip install seaborn)*
    - plotly — optional library for interactive and dynamic graphs *(pip install plotly)*
    - scikit-learn — for preprocessing, baseline ML models, and evaluation metrics *(pip install scikit-learn)*
- **Machine Learning & Deep Learning Tools**
    - torch (PyTorch) — primary framework for building, training, and deploying neural network models *(pip install torch)*

1. Purpose & Scope

- Guide for implementing and evaluating energy forecasting models from the *Final Report – Energy*. • Focuses on:
    - Dataset descriptions.
    - Preprocessing steps.
    - Models evaluated (no extra models added).
    - Key results and conclusions.

2. Datasets

2.1 SmartHome Environmental Time-Series Dataset •

Multivariate, minute-level sequential data. •

Features:

- Energy usage ("Appliances").
- Indoor temp/humidity (T1–T9, RH1–RH9).
- Outdoor weather (T_out, RH_out, wind speed, visibility, pressure).
- Date/time/day of week.

- Model used: **T-FormerReg (Time-Series)**.

2.2 Appliance-Level Household Energy Usage Dataset

- Structured, non-sequential tabular data.
- Features:
  - Appliance type, household size, season.
  - Outdoor temperature, timestamp details.
  - Mixed categorical & numerical.
- Model used: **T-FormerReg (Tabular)**.

3. Preprocessing

3.1 Time-Series Dataset

- Missing values → forward fill + interpolation.
- Temporal encoding → sine/cosine for periodicity.
- Normalization → Z-score standardization.
- Patterns:
  - Evening peak (17:00–19:00).
  - Higher consumption at high indoor temp.
  - Mild seasonal variation.

3.2 Tabular Dataset

- Categorical → embeddings.
- Numerical → min–max normalization.
- Time/date → discrete segments (hour blocks, weekday/weekend).
- Stratified train/val/test split by appliance type.

4. Models Evaluated

- **Machine Learning:**
  - XGBoost
  - LightGBM
  - KNN
  - Random Forest (SmartHome)

```python
import matplotlib.pyplot as plt
from lightgbm import LGBMRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import numpy as np


# Estimators parameter tuning
n_estimators_list = [50, 100, 120, 150]

mse_values = []
final_result = {}

print("LightGBM Estimator Tuning:\n")

for n_est in n_estimators_list:
    model = LGBMRegressor(
        n_estimators=n_est,
        learning_rate=0.001,
        max_depth=3,
        num_leaves=10,
        random_state=42
    )
    model.fit(X_train, y_train)
    preds = model.predict(X_test)

    mse = mean_squared_error(y_test, preds)
    mae = mean_absolute_error(y_test, preds)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, preds)
```

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Light GBM

- **Deep Learning:**
    - Deep MLP (SmartHome)
    - FFNN (Appliance-level)
    - CNN

```python
# Preprocessing
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled = np.expand_dims(X_scaled, axis=2)  # (samples, features, 1)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
y_train_noisy = y_train + np.random.normal(0, 2.0, size=y_train.shape)

# Tuning configurations
configs = [(4, 2), (8, 3), (16, 5)]
mse_scores = []
labels = []

print("Tuning CNN configurations:\n")

for filters, kernel in configs:
    model = Sequential([
        Conv1D(filters=filters, kernel_size=kernel, activation='relu', input_shape=(X_train.shape[1], 1)),
        Flatten(),
        Dense(1)
    ])
    model.compile(optimizer='adam', loss='mse', metrics=['mae'])
    model.fit(X_train, y_train_noisy, epochs=8, batch_size=64, verbose=0)

    y_pred = model.predict(X_train)
```

CNN Model

- **Hybrid (Main Model):**

○ **T-FormerReg (Time-Series)** ○ **T-FormerReg (Tabular)**

```
# Model Architecture
input_layer = Input(shape=(1, X_scaled.shape[2]))
x = transformer_encoder(input_layer)
x = GlobalAveragePooling1D()(x)
x = Dense(64, activation="relu")(x)
x = Dropout(0.1)(x)
output_layer = Dense(1)(x)

model_transformer = Model(inputs=input_layer, outputs=output_layer)

# Compile and train with tracking MSE and MAE
model_transformer.compile(optimizer="adam", loss="mse", metrics=["mae"])

history = model_transformer.fit(X_train, y_train, epochs=15, batch_size=32, validation_split=0.1)

# Get MSE and MAE values from history
mse_values = history.history['loss']
mae_values = history.history['mae']

# Plot MSE and MAE vs Epochs
epochs = range(1, len(mse_values) + 1)

plt.figure(figsize=(12, 6))
```

5. Key Results

5.1 SmartHome Time-Series

- Best: **T-FormerReg** → MSE 2.19, R^2 0.37.
- Outperformed all baselines in capturing temporal patterns.

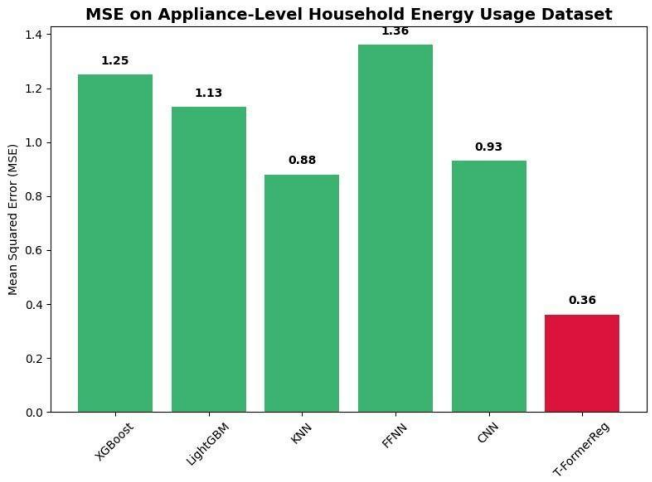
5.2 Appliance-Level Tabular

- Best: **T-FormerReg** → MSE 0.36, R^2 0.74.
- Strong contextual feature learning without heavy computation.

```
Transformer Regression Model:
MSE: 0.361826
MAE: 0.487219
RMSE: 0.601519
R²: 0.742754
```

6. Insights

- ML baselines → solid, but weak temporal/contextual awareness. • Deep learning → better representations, but higher complexity.
- Transformers → best accuracy + efficiency + adaptability.



References

Core Programming and Data Libraries

- https://docs.python.org/3/
- https://numpy.org/doc/
- https://pandas.pydata.org/docs/
- https://scikit-learn.org/stable/documentation.html

Deep Learning Frameworks

- https://pytorch.org/docs/stable/index.html
- https://www.tensorflow.org/api_docs/python/tf/keras

Ensemble Learning & Gradient Boosting

- https://lightgbm.readthedocs.io/en/latest/
- https://xgboost.readthedocs.io/en/stable/

Data Visualization Tools

- https://matplotlib.org/stable/users/index.html
- https://seaborn.pydata.org/
- https://plotly.com/python/

Development & Experimentation Environments

- https://jupyter.org/documentation