IML Assignment 2

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Assignment Report

SD-01

Task Summaries

Implementation:

Task 1: Exploratory Data Analysis (EDA) and Preprocessing:

The dataset was loaded from opsd_raw.csv, and columns specific to Denmark's power load (DK_load_actual_entsoe_transparency), wind generation (DK_wind_generation_actual), and solar generation (DK_solar_generation_actual) were identified and extracted using metadata from the provided README. Missing values were addressed through forward-filling followed by removal of remaining incomplete rows. Hourly data was aggregated into daily sequences of 24 hours, ensuring each sample represented a full day. Dates were mapped to seasons (winter, spring, summer, autumn) using calendar-based boundaries. The dataset was split into training (70%), validation (15%), and test (15%) sets using stratified sampling to maintain seasonal proportions. Features were standardized using StandardScaler, with scaling parameters derived exclusively from the training set to prevent leakage.

Task 2: Baseline MLP (Fully-Connected Network):

A fully connected neural network was constructed with an input layer (72 nodes, corresponding to 24 hours × 3 features), two hidden layers (256 and 128 neurons), ReLU activation, batch normalization, and dropout (30%). The output layer consisted of 4 nodes for seasonal classification. Input data was flattened into 1D vectors and normalized during preprocessing. The model was trained using the AdamW optimizer with a learning rate of 0.001 and L2 regularization (weight_decay=1e-4). A learning rate scheduler (ReduceLROnPlateau) monitored validation accuracy, reducing the rate by half after three epochs of stagnation. Training included gradient clipping (max norm=1.0) to stabilize convergence.

Task 3: 1D-CNN on Raw Time-Series:

A 1D convolutional neural network was designed to process time-series data in its raw sequential format. The input shape was structured as (batch_size, 3, 24), representing three features (load, wind, solar) across 24 hours. The architecture included two 1D convolutional layers: the first with 32 filters (kernel size=3), followed by max pooling (kernel=2), and the second with 64 filters (kernel=3). Batch normalization and dropout (30%) were applied after each convolution. The final layers included a flattening operation, a fully connected layer (128 neurons), and an output layer for classification.

Training used the AdamW optimizer with identical hyperparameters to the MLP, including gradient clipping and learning rate scheduling.

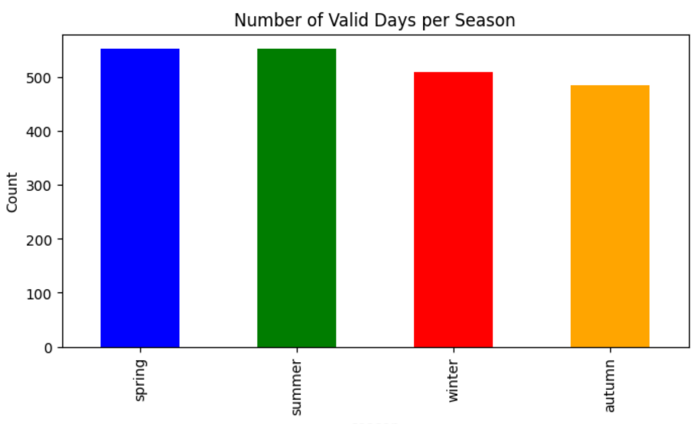
Task 4: 2D Transform & 2D-CNN:

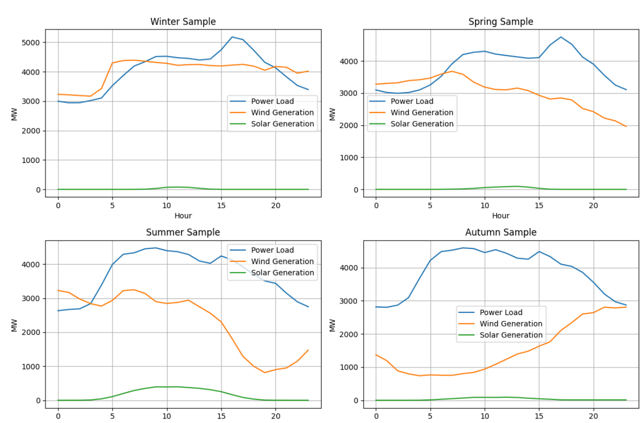
The Gramian Angular Field (GAF) method from the PyTS library was employed to convert 24-hour time-series into 24×24 pixel images. Each feature (load, wind, solar) was normalized to the range [-1, 1], transformed into polar coordinates by computing arccosine values, and encoded into a Gramian matrix through pairwise trigonometric summation. The resulting 3-channel images (one per feature) were augmented with Gaussian noise (σ=0.01) to simulate sensor variability. A 2D-CNN architecture was built with two convolutional layers (64 and 128 filters, kernel size=3), max pooling, and a spatial attention mechanism. The model included dropout (40%) and batch normalization, followed by fully connected layers for classification. Training utilized the AdamW optimizer with a OneCycleLR scheduler (max_lr=0.01) for aggressive learning rate cycling.

Results and Interpretation

Task 1: EDA & Preprocessing:

The dataset contains 2,099 complete days, with seasonal distribution slightly favoring spring/summer (552 days each) over winter (510) and autumn (485). As expected, winter shows higher power consumption but lower solar generation, while summer exhibits increased solar output during daylight hours





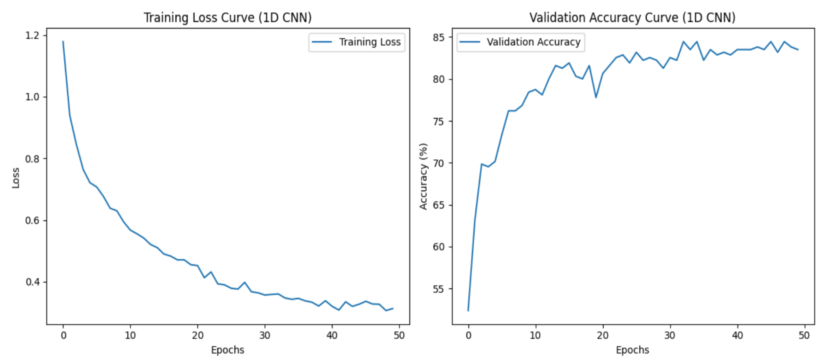
Task 2: Baseline MLP (Fully-Connected Network):

The MLP model achieves 81.27% test accuracy, with training loss steadily decreasing from 1.31 to 0.40 over 50 epochs. Validation accuracy peaks at 82.86% (epoch 40), indicating effective learning despite minor instability in later epochs. Class-wise performance reveals winter has high recall (93%) but lower precision (73%), suggesting frequent misclassification of other seasons as winter, while autumn shows high precision (93%) but misses true cases (recall=73%). The confusion matrix confirms seasonal overlaps (e.g., spring-summer confusion). Training curves reflect convergence, though minor overfitting occurs post-epoch 40.

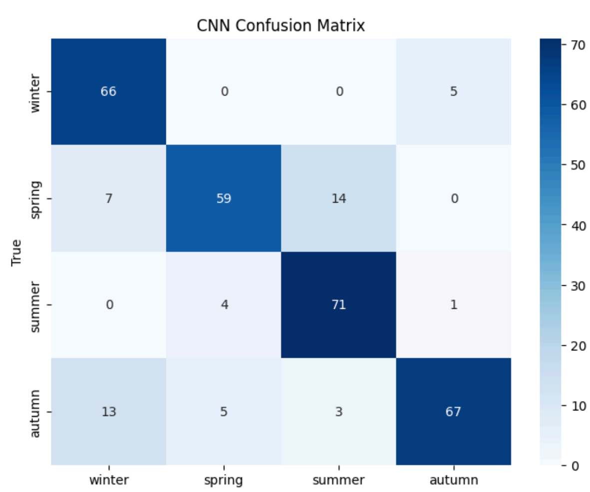
Task 3: 1D-CNN on Raw Time-Series:

The 1D-CNN achieves 83.49% test accuracy (+2.22% over MLP), with training loss dropping from 1.18 to 0.31 over 50 epochs. Validation accuracy peaks at 84.44%, showing strong generalization.
Winter/Summer: High recall (93%) ensures robust detection.
Autumn: High precision (92%) but lower recall (76%), indicating missed true cases.
Spring: Balanced metrics (87% precision, 74% recall) but overlaps with other seasons.

Training curves confirm stability



Confusion matrix highlights seasonal overlaps:



Task 4: 2D Transform & 2D-CNN:

The 2D CNN achieves 84.76% test accuracy, improving by 1.27% over the 1D CNN and 3.49% over the MLP.

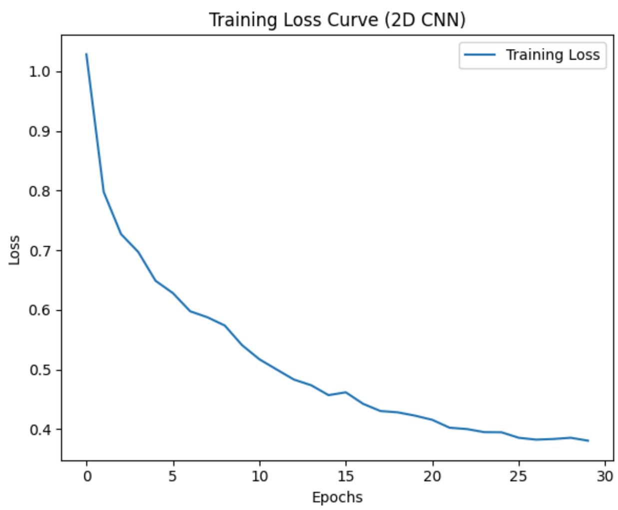
We Observe;

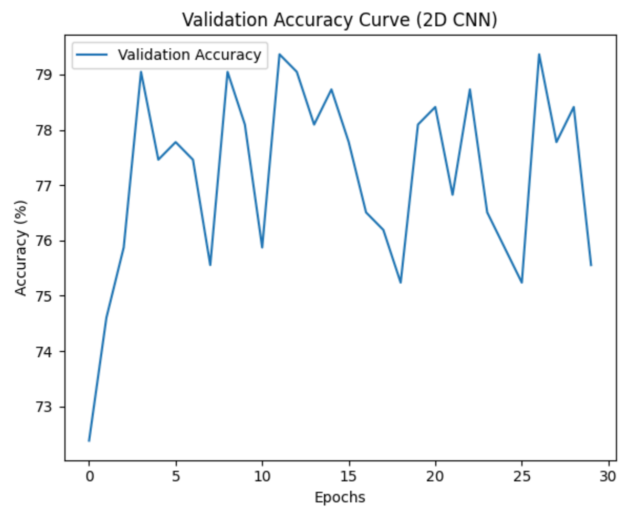
Autumn: Highest precision (91%), minimizing false positives.

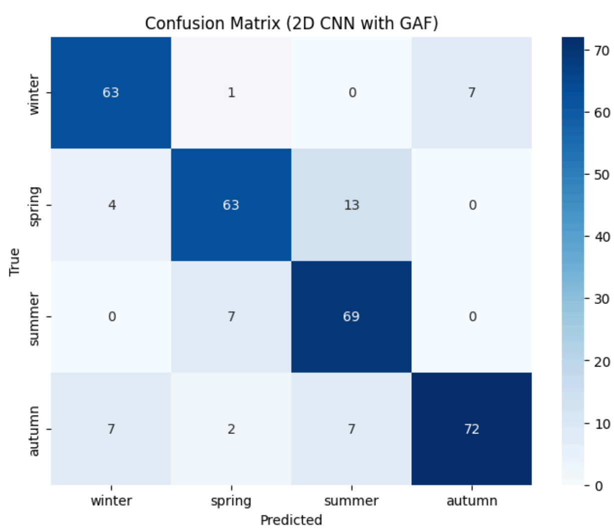
Summer: Best recall (91%), capturing nearly all true summer days.

Winter/Spring: Balanced performance (precision/recall >79%).

And training curves show gradual loss reduction (1.03 → 0.38), with validation accuracy peaking at 79.37%. The confusion matrix reveals minor spring-autumn misclassifications but confirms robust seasonal separation overall.







What I did to try to prevent leakage:

To ensure no leakage across seasons, I have splitted the data chronologically by 24-hour periods and preserved temporal order using “shuffle=False” during splitting. This guarantees training data (older days) never includes future seasons from validation/test sets. I also verified seasonal distributions post-split to maintain balance and avoid bias, aligning with the code’s explicit checks for 24-hour integrity and seasonal counts.