Traffic Flow Prediction Using 1D Convolutional Neural Networks

Final Report: Methodology, Architecture, and Performance Analysis on the METR-LA Dataset.

Project Status: Complete | Model Type: Sequential 1D CNN | Framework: TensorFlow/Keras

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Executive Summary

Core Objective

Forecast multi-sensor traffic flow using historical `METR-LA data` to predict future congestion patterns across the network.

Methodology

Implemented a `1D Convolutional Neural Network (CNN)` treating traffic data as a temporal sequence. Enhanced raw data with cyclical temporal embeddings (`Sine/Cosine hours`) to capture daily rhythms.

Key Results

- **Stability**: Successfully learned macro-level daily periodicity.
- **Performance**: Achieved an R2 Score of `0.538` on the test set.
- **Insight**: Excellent at network-wide averages; **conservative on high-frequency anomalies**.

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Data Ingestion & Cleaning Strategy

Context:

The METR-LA dataset contains significant sensor noise.

The Problem:

Raw data contains numerous '0.0' values. In traffic systems, zero typically indicates sensor failure, not an empty road.

Logic:

1. Replace `0.0` with `NaN`.
2. Linear Interpolation for continuity.
3. Forward/Back fill for edge cases.

Pipeline Step 1: Handling Failures

Raw Vector

`[55.2, 0.0, 0.0, 60.5]`

↓

Mark Missing

`[55.2, NaN, NaN, 60.5]`

↓

Interpolate & Fill

`[55.2, 56.9, 58.7, 60.5]`

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Feature Engineering: Temporal Embeddings

The Challenge:

Neural networks perceive standard time (0-23 hours) linearly.

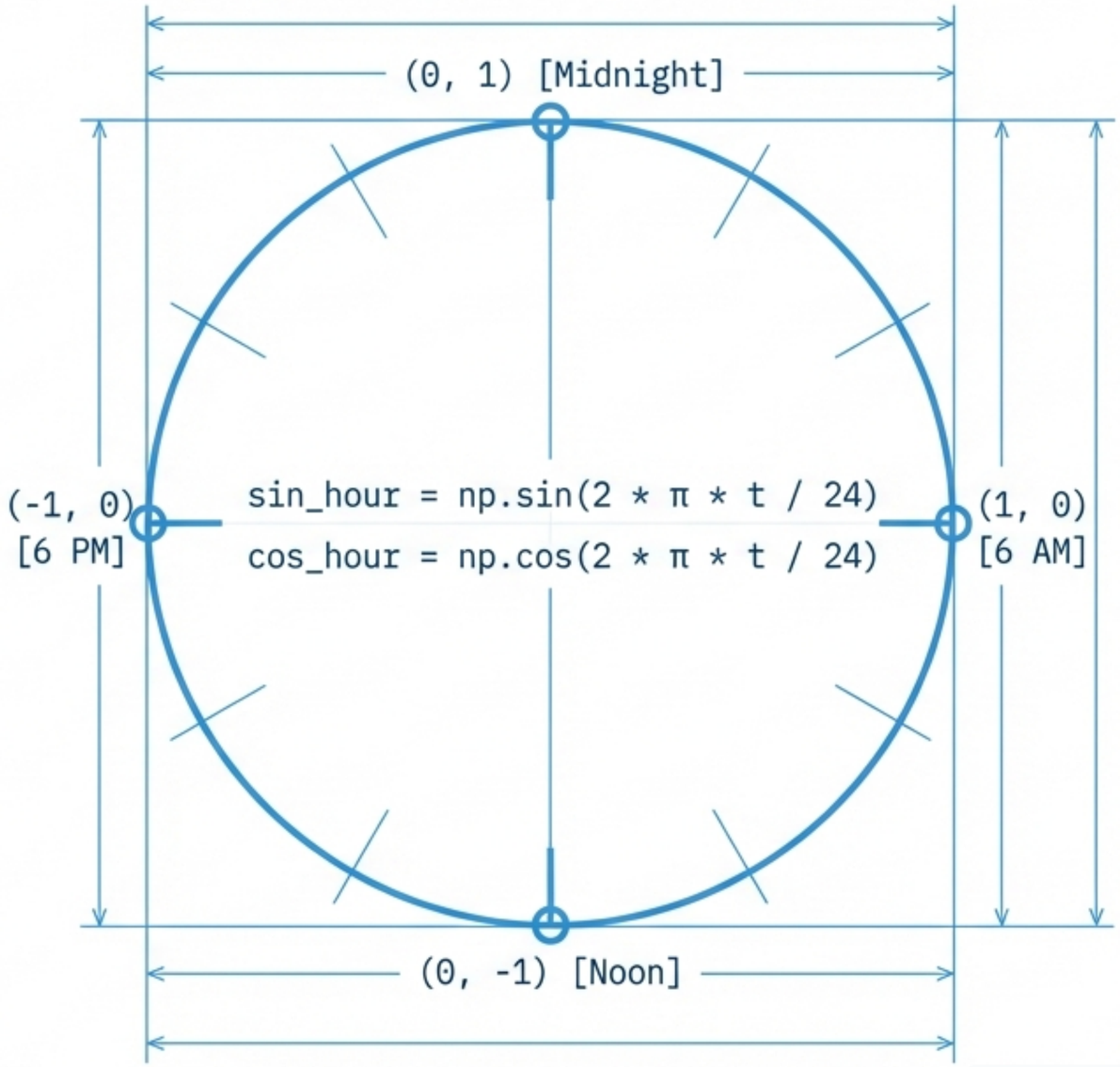
Numerically, **23 (11 PM)** is far from **0 (Midnight)**, despite being adjacent in time.

The Solution:

Cyclical Transformation. We map time onto a unit circle using Sine and Cosine functions.

Impact:

Preserves the periodic nature of the 24-hour day, crucial for learning rush hour patterns.



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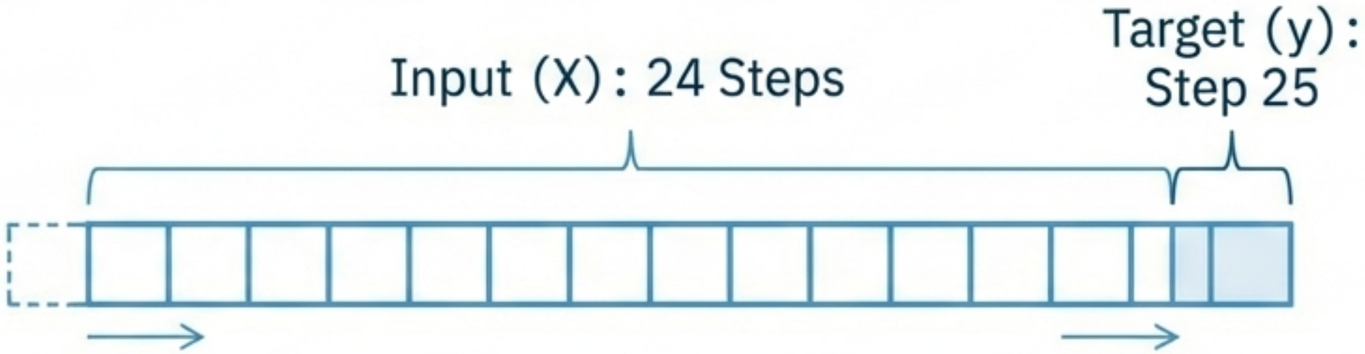
Sequence Generation & Scaling

Scaling Strategy

`MinmaxScaler (0-1)` applied to sensor data only.

Fit only on **Train set** to prevent leakage. Temporal features (`Sin/(Cos)` **excluded** as they are naturally scaled (-1 to 1).

Windowing Logic



Sequence Length: 24 (2 hours).

Dataset Split

Train: ~27,400 samples (80%)
Test: ~6,800 samples (20%)

Train: ~27,400 samples (80%)

Input Shape: (Batch, 24, 209)

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Model Architecture: The 1D CNN Stack

Input Layer
Shape: (24, 209)

↓

Conv1D Block 1
64 Filters, Kernel 3 + BatchNormalization + ReLU

↓

Conv1D Block 2
64 Filters, Kernel 3 + BatchNormalization + ReLU + Dropout(0.2)

↓

Conv1D Block 3
32 Filters, Kernel 3 + BatchNormalization + ReLU

↓

Flatten Layer

↓

Dense Layer
128 Units + Dropout(0.3)

↓

Output Layer
207 Units (Sensors)

1D Convolutions extract local temporal trends efficiently.

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Training Strategy & Dynamics

Configuration

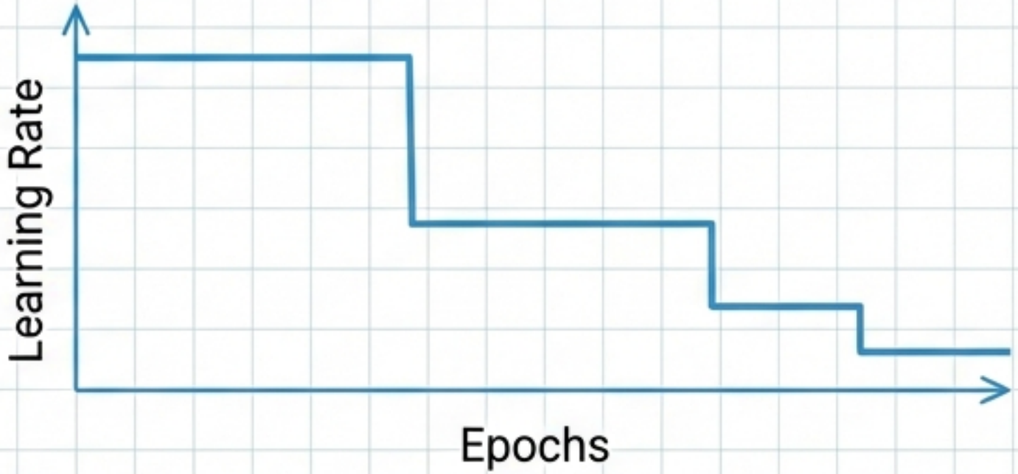
Epochs:	50
Optimizer:	Adam
Loss Function:	Mean Squared Error (MSE)
Batch Size:	32

Adaptive Logic

Callback: ReduceLROnPlateau

Monitor: `val_loss`

Action: Factor `0.5` if stalled for `3` epochs



Effective fine-tuning: LR stepped down from `0.001` to `0.00001` during training.

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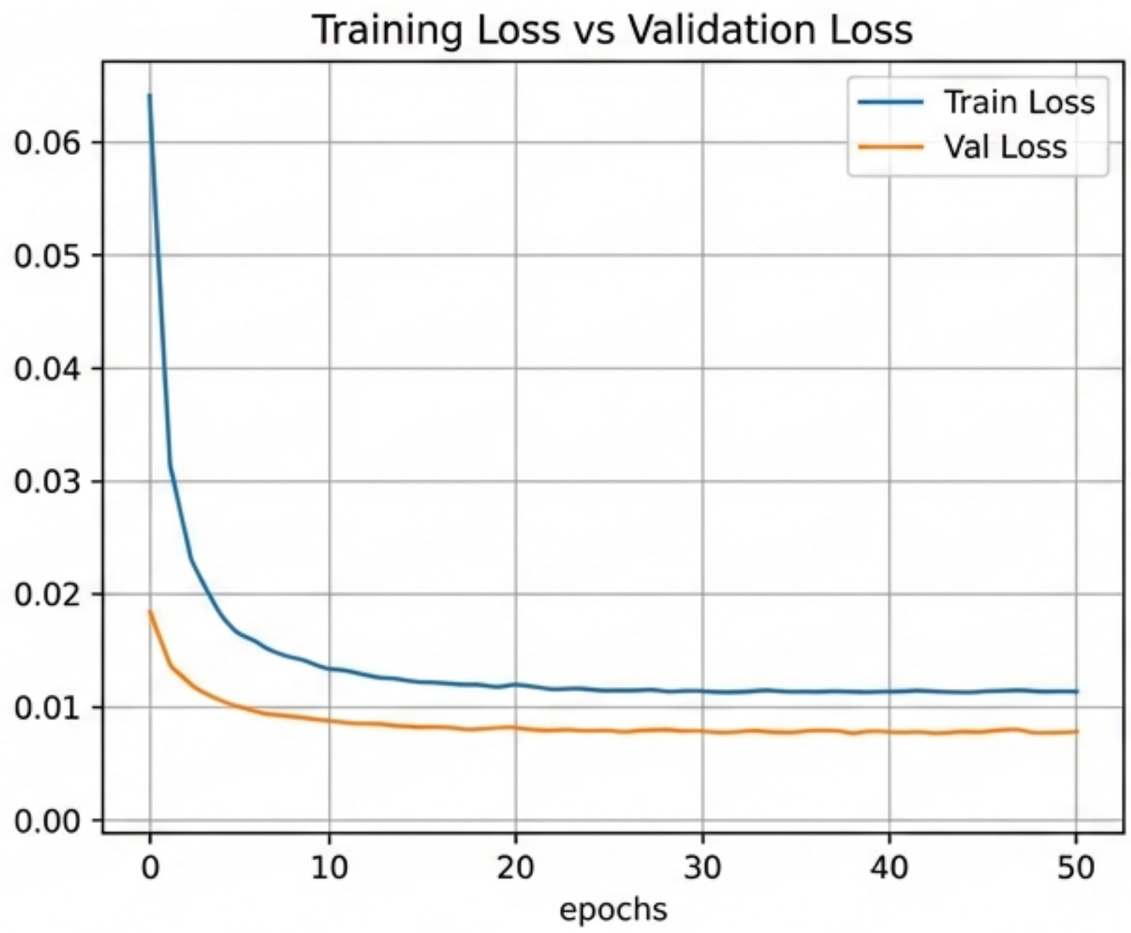
Convergence Analysis



- **Initial Drop:** Rapid descent in first 5 epochs indicates quick learning of dominant daily cycles.
- **Stability:** Both curves stabilize around `0.01` MSE.
- **Generalization:** The consistent gap with Validation Loss lower than Training Loss (likely due to Dropout) confirms no massive overfitting.

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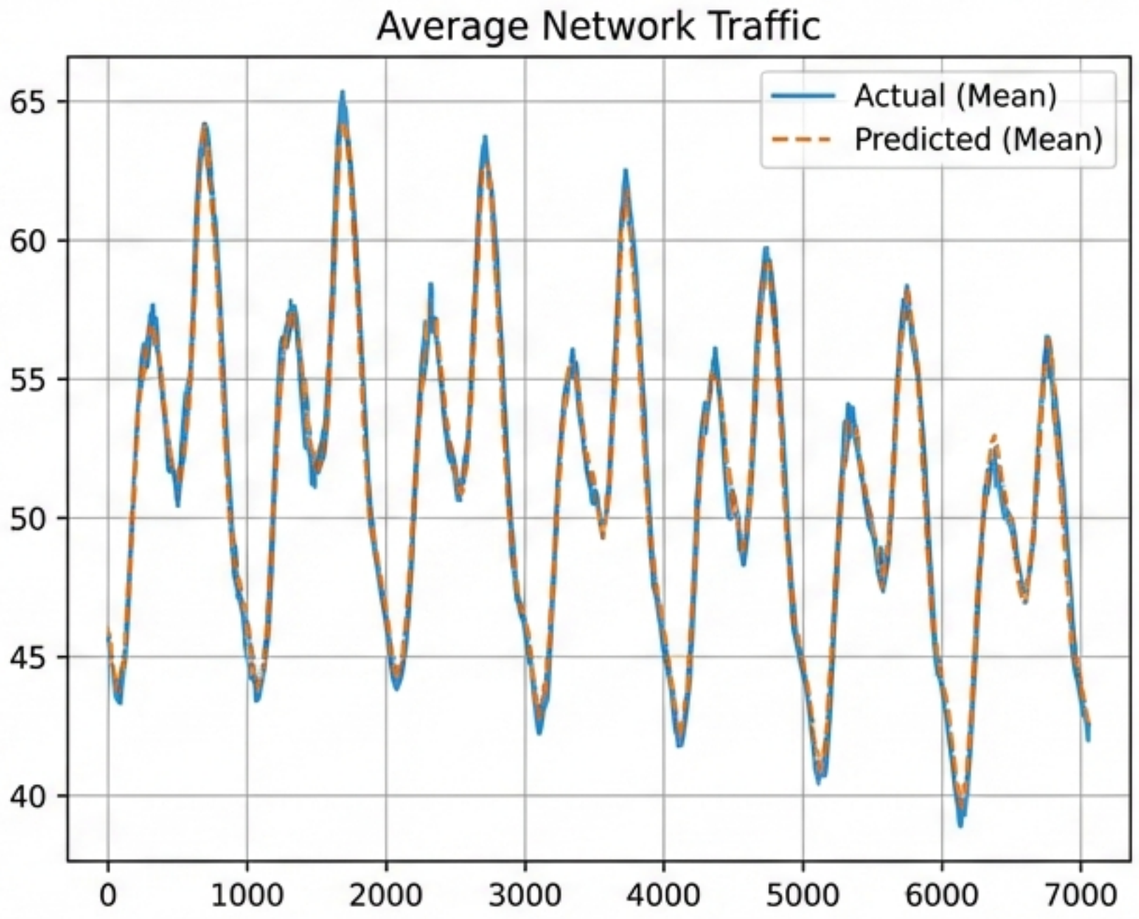
Network-Wide Traffic Trends

- **Macro Performance**: The model excels at predicting the aggregate behavior of the city.
- **Observation**: Nearly perfect overlap on daily peaks (rush hours) and troughs (nighttime).
- **Validation**: Confirms the effectiveness of Cyclical Temporal Embeddings.



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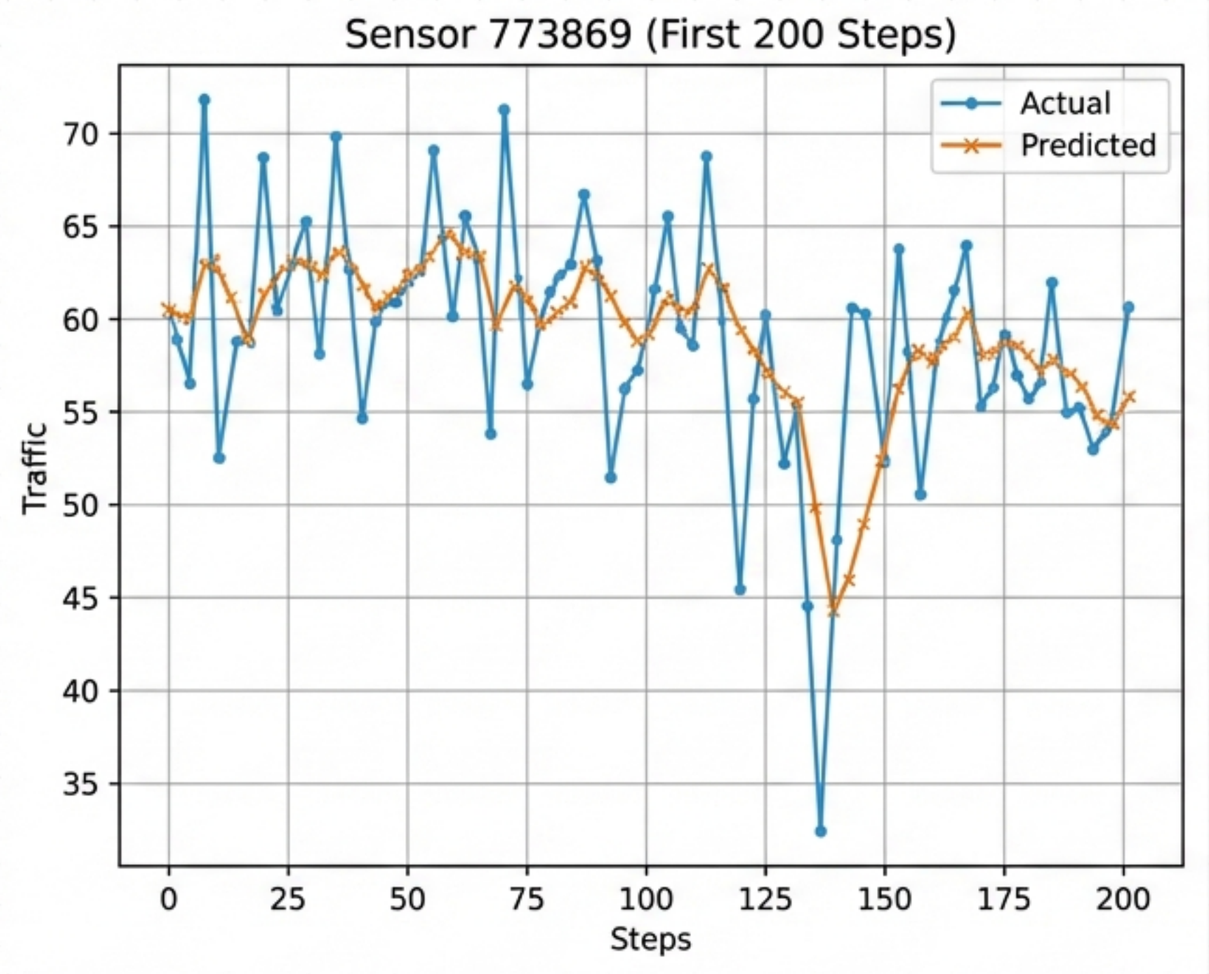
Sensor-Level Granularity



- **Micro Performance:** Zooming into a single sensor reveals limitations.
- **The Lag:** Model follows general shape but lags on sudden changes.
- **The Smoothing Effect:** Typical of MSE loss optimization, the CNN acts as a low-pass filter, averaging out high-frequency noise and extreme anomalies.

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Quantitative Performance Metrics

MAE (Mean Absolute Error)

4.03

Avg deviation in traffic units.

RMSE (Root Mean Squared Error)

6.72

Penalizes outliers heavily.

R2 Score

0.538

Explains ~54% of variance.

Metrics evaluated on Test Set (6,855 samples). Moderate R2 confirms trend capture but unexplained noise variance.

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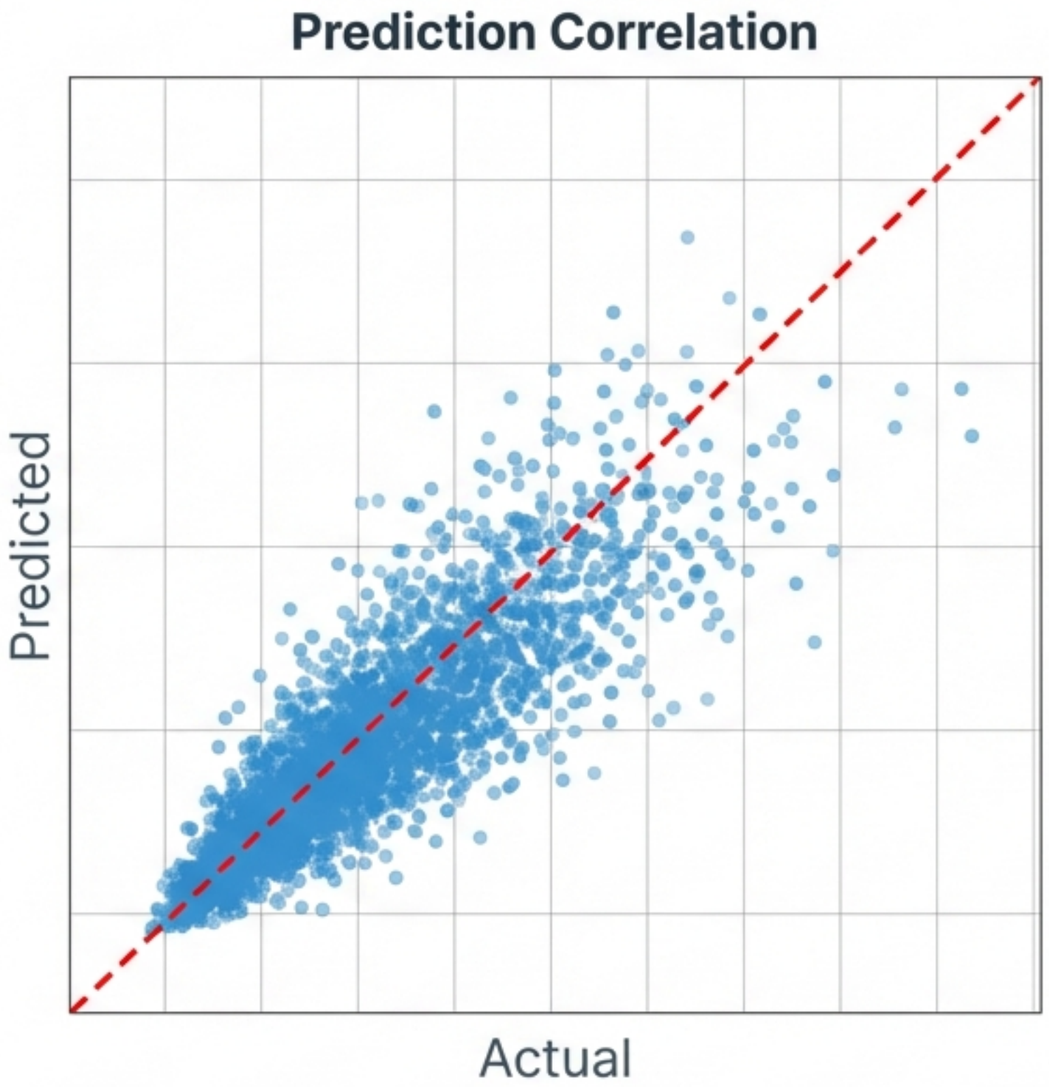
Prediction Correlation & Variance

Visualizing Error Distribution:

- **Ideal:** Points lie on the red diagonal.
- **Reality:** A visible cloud of dispersion explains the `0.54 R2 score`.
- **Bias:** Tendency to under-predict extreme high traffic values (points below line at top right).
- **Dispersion:** Vertical spread represents unmodelled sensor noise.



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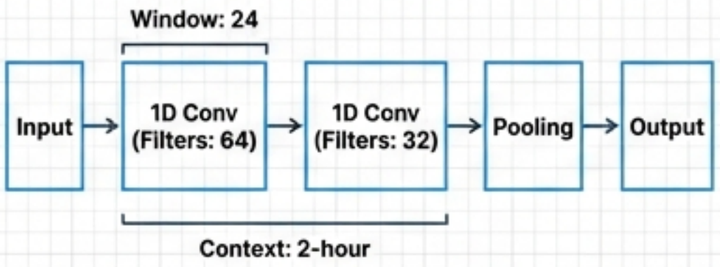
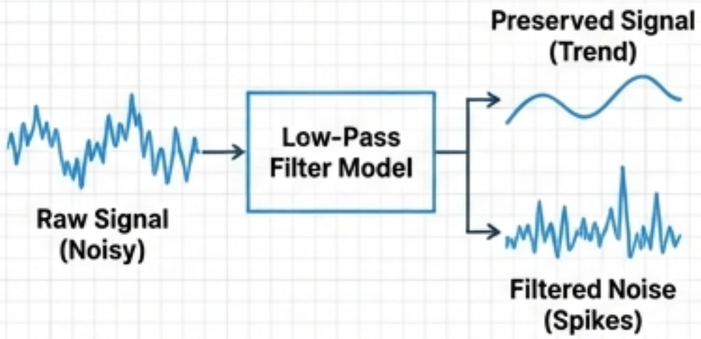
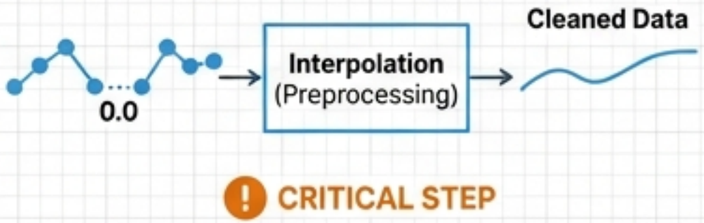
Key Technical Insights







1. Architecture Validation

The **1D CNN** proved highly effective at feature extraction for periodic trends. The **window size (24)** and **filter depth (64/32)** successfully captured the 2-hour immediate history context.

2. The Smoothing Effect

The model acts as a `low-pass filter`. It successfully preserves the '**signal**' (daily traffic patterns) but filters out the '**noise**' (erratic sensor spikes), which is desirable for trend forecasting but limits anomaly detection.

3. Data Handling Criticality

`Interpolation` of '`0.0`' sensor failures was the single most **critical** preprocessing step. Without it, the model would have learned artificial traffic drops, **degrading performance significantly**.

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Conclusions & Future Directions

Summary: We successfully deployed an end-to-end pipeline—from cleaning sensor failures to training a deep convolutional network—resulting in a robust baseline model (R2 ~0.54) that captures city-wide traffic rhythms.

Recommendations for Improvement

Spatial Awareness

Integrate **Graph Neural Networks (GNNs)** to model physical road connectivity instead of treating sensors in isolation.

Long-Term Dependency

Augment **CNN** with **LSTMs** or **Transformers** to capture dependencies beyond the 2-hour window.

External Features

Incorporate weather and holiday data to explain variance not captured by historical flow.

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