```
import pandas as pd
# Load the CSV file
file_path = "/content/traffic_data_dyn (1).csv"
df = pd.read_csv(file_path)
# Display basic info
print(df.info()) # Check column names and data types
print(df.head()) # Preview first few rows
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 86635 entries, 0 to 86634
     Data columns (total 12 columns):
          Column
                                       Non-Null Count Dtype
     ---
          -----
      0
          Time
                                       86635 non-null float64
          Vehicle Count at Junction A 86635 non-null int64
      1
          Vehicle Count at Junction B 86635 non-null int64
      3
          Vehicle Count at Junction C 86635 non-null int64
      4
          Vehicle Count at Junction D 86635 non-null int64
      5
          Vehicle Count at Junction E 86635 non-null int64
      6
          Avg Speed on AB
                                       86635 non-null float64
                                       86635 non-null float64
      7
          Avg Speed on BC
                                       86635 non-null float64
      8
          Avg Speed on CA
      9
          Avg Speed on CD
                                       86635 non-null float64
      10
         Avg Speed on ED
                                       86635 non-null float64
      11 Avg Speed on DA
                                       86635 non-null float64
     dtypes: float64(7), int64(5)
     memory usage: 7.9 MB
     None
        Time Vehicle Count at Junction A Vehicle Count at Junction B
     0
         1.0
                                        0
                                                                      0
                                                                      0
     1
         2.0
                                        0
                                        0
                                                                      0
     2
         3.0
     3
         4.0
                                        0
                                                                      0
     4
         5.0
                                         0
                                                                      0
        Vehicle Count at Junction C Vehicle Count at Junction D
     0
     1
                                  0
                                                                0
     2
                                  0
                                                                0
     3
                                  0
                                                                0
                                                                0
     4
                                  0
        Vehicle Count at Junction E Avg Speed on AB Avg Speed on BC
     0
                                  0
                                                  0.0
                                                              0.000000
     1
                                  0
                                                  0.0
                                                              0.000000
     2
                                  0
                                                  0.0
                                                              2.181660
     3
                                  0
                                                  0.0
                                                              4.622117
     4
                                  0
                                                  0.0
                                                              6.796626
        Avg Speed on CA Avg Speed on CD Avg Speed on ED Avg Speed on
     0
                    0.0
                                     0.0
                                                       0.0
                                                                   0.000
     1
                    0.0
                                     0.0
                                                       0.0
                                                                   1.317
     2
                    0.0
                                     0.0
                                                       0.0
                                                                   3.199
     3
                    0.0
                                     0.0
                                                       0.0
                                                                   5.222
     4
                    0.0
                                      0.0
                                                       0.0
                                                                   6.901
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.model selection import train test split
# Load Data
file_path = "/content/traffic_data_dyn (1).csv"
df = pd.read_csv(file_path)
```

Resources X

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At your current usage level, this runtime may last up to 1 hour 40 minutes.

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Not connected to runtime.

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```
# Select features and target
features = [
    "Vehicle Count at Junction A", "Vehicle Count at Junction B",
    "Vehicle Count at Junction D", "Vehicle Count at Junction E",
    "Avg Speed on AB", "Avg Speed on BC", "Avg Speed on CA",
    "Avg Speed on CD", "Avg Speed on ED", "Avg Speed on DA"
target = "Vehicle Count at Junction C"
# Normalize data
scaler = MinMaxScaler()
df scaled = scaler.fit transform(df[features + [target]])
# Convert to NumPy
df_scaled = np.array(df_scaled)
# Define sequence length
SEQ_LENGTH = 5 # Reduce to save memory
# Use NumPy array slicing for efficient sequence creation
X = np.array([df_scaled[i:i+SEQ_LENGTH, :-1] for i in range(len(df_sca
y = np.array([df_scaled[i+SEQ_LENGTH, -1] for i in range(len(df_scaled
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
print("Optimized Shape - X_train:", X_train.shape, "y_train:", y_train
→ Optimized Shape - X_train: (69304, 5, 10) y_train: (69304,)
import tensorflow as tf
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Activation
# Define Pelliot activation function
def pelliot_activation(x, a=0.5):
    return x / (1 + a * K.abs(x))
# Create a custom activation layer
class PelliotActivation(Activation):
    def __init__(self, activation, **kwargs):
        super(PelliotActivation, self).__init__(activation, **kwargs)
        self.__name__ = 'pelliot_activation'
# Register the activation
tf.keras.utils.get custom objects().update({'pelliot activation': Pell
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
# Build the LSTM Model
model = Sequential([
    LSTM(64, return_sequences=True, input_shape=(SEQ_LENGTH, X_train.s
    LSTM(32, return_sequences=False),
    Dense(16, activation=PelliotActivation(pelliot_activation)), # Pe
    Dense(1) # Output layer (vehicle count)
1)
# Compile the model
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
# Summary
model.summary()
```



/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.p super().__init__(**kwargs)
Model: "sequential_1"

Layer (type)	Output Shape
lstm_2 (LSTM)	(None, 5, 64)
lstm_3 (LSTM)	(None, 32)
dense_2 (Dense)	(None, 16)
dense_3 (Dense)	(None, 1)

Total params: 32,161 (125.63 KB) **Trainable params:** 32,161 (125.63 KB)

```
# Train the model
history = model.fit(X_train, y_train, epochs=200, batch_size=32, valid
# Plot training loss
import matplotlib.pyplot as plt
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.title("Loss Curve")
plt.show()
```

÷	French 4 (200							
→ ▼	Epoch 1/200 2166/2166 ———————————————————————————————————	18s	7ms/step	_	loss:	0.0244	_	mae:
	Epoch 2/200							
	2166/2166 ———————————————————————————————————	20s	7ms/step	-	loss:	0.0185	-	mae:
	Epoch 3/200 2166/2166	21s	8ms/step	_	loss:	0.0180	_	mae:
	Epoch 4/200							
	2166/2166 — Epoch 5/200	20s	7ms/step	-	loss:	0.0176	-	mae:
	·	15s	7ms/step	-	loss:	0.0173	-	mae:
	Epoch 6/200		_ , .		_			
	2166/2166 Epoch 7/200	21s	7ms/step	-	loss:	0.0171	-	mae:
	2166/2166	20s	7ms/step	-	loss:	0.0164	-	mae:
	Epoch 8/200	100	7ms/stan		1000	0.0150		
	2166/2166 Epoch 9/200	102	7ms/step	-	1055.	0.0138	_	mae:
	2166/2166 ————	20s	7ms/step	-	loss:	0.0159	-	mae:
	Epoch 10/200 2166/2166 ———————————————————————————————————	160	8ms/step	_	1000	0 0155		m20:
	Epoch 11/200	103	ollis/scep	_	1033.	0.0155	_	mae.
		19s	7ms/step	-	loss:	0.0152	-	mae:
	Epoch 12/200 2166/2166 ———————————————————————————————————	16s	7ms/step	_	loss:	0.0151	_	mae:
	Epoch 13/200							
	2166/2166 Epoch 14/200	19s	7ms/step	-	loss:	0.0150	-	mae:
		21s	7ms/step	_	loss:	0.0147	_	mae:
	Epoch 15/200	4.	0 / 1			0 04 47		
	2166/2166 Epoch 16/200	1/5	8ms/step	-	loss:	0.0147	_	mae:
	2166/2166	20s	7ms/step	-	loss:	0.0144	-	mae:
	Epoch 17/200 2166/2166 ———————————————————————————————————	21.0	8ms/step		10551	0 0142		mao:
	Epoch 18/200	215	oms/scep	-	1055:	0.0143	_	mae:
		16s	7ms/step	-	loss:	0.0141	-	mae:
	Epoch 19/200 2166/2166 ———————————————————————————————————	21s	8ms/step	_	loss:	0.0139	_	mae:
	Epoch 20/200		·					
	2166/2166 Epoch 21/200	21s	8ms/step	-	loss:	0.0135	-	mae:
	•	20s	8ms/step	_	loss:	0.0135	_	mae:
	Epoch 22/200					0.0430		
	2166/2166 Epoch 23/200	205	8ms/step	-	loss:	0.0132	-	mae:
	2166/2166	17s	8ms/step	-	loss:	0.0132	-	mae:
	Epoch 24/200 2166/2166 ———————————————————————————————————	21 c	8ms/step	_	1000	0 0130		mao:
	Epoch 25/200	213	ollis/scep	_	1033.	0.0130	_	iliae.
	2166/2166	21s	8ms/step	-	loss:	0.0128	-	mae:
	Epoch 26/200 2166/2166 ———————————————————————————————————	18s	8ms/step	_	loss:	0.0124	_	mae:
	Epoch 27/200		•					
	2166/2166 — Epoch 28/200	21s	8ms/step	-	loss:	0.0123	-	mae:
		18s	7ms/step	_	loss:	0.0122	_	mae:
	Epoch 29/200	226	Ome/ston		10551	0 0120		mao.
	2166/2166 Epoch 30/200	225	8ms/step	-	1055;	0.0120	_	mae:
	2166/2166 ————	20s	8ms/step	-	loss:	0.0118	-	mae:
	Epoch 31/200 2166/2166 ———————————————————————————————————	17c	8ms/step		1000	0 0117	_	mae.
	Epoch 32/200	1/3	ошэ, эсср		1033.	0.0117		mac.
		19s	7ms/step	-	loss:	0.0114	-	mae:
	Epoch 33/200 2166/2166 ———————————————————————————————————	17s	8ms/step	_	loss:	0.0115	_	mae:
	Epoch 34/200		·					
	2166/2166 Epoch 35/200	21s	8ms/step	-	loss:	0.0111	-	mae:
	2166/2166	17s	8ms/step	-	loss:	0.0110	-	mae:
	Epoch 36/200	47-	Om = / = 1		1	0.0100		m
	2166/2166 Epoch 37/200	T/S	oms/step	-	TO22:	0.0108	-	mae:
	The state of the s	15s	7ms/step	-	loss:	0.0106	-	mae:

Epoch 38/200	46-	0 - /-1		1	0.0104		
2166/2166 — Epoch 39/200	165	8ms/step	-	loss:	0.0104	_	mae:
2166/2166 — Epoch 40/200	19s	7ms/step	-	loss:	0.0104	-	mae:
2166/2166	20s	7ms/step	-	loss:	0.0101	-	mae:
Epoch 41/200 2166/2166 ———————————————————————————————————	22s	8ms/step	-	loss:	0.0099	_	mae:
Epoch 42/200 2166/2166 ———————————————————————————————————	15s	7ms/step	_	loss:	0.0098	_	mae:
Epoch 43/200							
Epoch 44/200		7ms/step					
2166/2166 ———————————————————————————————————	20s	7ms/step	-	loss:	0.0095	-	mae:
2166/2166 —————	16s	7ms/step	-	loss:	0.0094	-	mae:
Epoch 46/200 2166/2166 ———————————————————————————————————	17 s	8ms/step	-	loss:	0.0092	_	mae:
Epoch 47/200 2166/2166 ———————————————————————————————————	15s	7ms/step	_	loss:	0.0090	_	mae:
Epoch 48/200							
Epoch 49/200		7ms/step					
2166/2166 — Epoch 50/200	16s	7ms/step	-	loss:	0.0088	-	mae:
2166/2166 ———————————————————————————————————	19s	7ms/step	-	loss:	0.0087	-	mae:
2166/2166 —————	22s	8ms/step	-	loss:	0.0086	-	mae:
Epoch 52/200 2166/2166 —————	21s	8ms/step	_	loss:	0.0085	_	mae:
Epoch 53/200 2166/2166 ———————————————————————————————————	195	7ms/sten	_	loss:	0.0083	_	mae:
Epoch 54/200							
Epoch 55/200		7ms/step					
2166/2166 — Epoch 56/200	21s	7ms/step	-	loss:	0.0081	-	mae:
2166/2166 — Epoch 57/200	20s	7ms/step	-	loss:	0.0079	-	mae:
2166/2166 —————	16s	7ms/step	-	loss:	0.0079	-	mae:
Epoch 58/200 2166/2166 ———————————————————————————————————	20s	7ms/step	_	loss:	0.0078	_	mae:
Epoch 59/200 2166/2166 ———————————————————————————————————	21s	7ms/step	_	loss:	0.0076	_	mae:
Epoch 60/200 2166/2166 ———————————————————————————————————							
Epoch 61/200							
Epoch 62/200		7ms/step					
2166/2166 — Epoch 63/200	21s	7ms/step	-	loss:	0.0073	-	mae:
2166/2166 — — — Epoch 64/200	19s	7ms/step	-	loss:	0.0072	-	mae:
2166/2166	21s	7ms/step	_	loss:	0.0072	_	mae:
Epoch 65/200 2166/2166 ———————————————————————————————————	21s	7ms/step	_	loss:	0.0071	_	mae:
Epoch 66/200 2166/2166 ———————————————————————————————————							
Epoch 67/200 2166/2166							
Epoch 68/200							
2166/2166 — Epoch 69/200	21s	8ms/step	-	loss:	0.0069	-	mae:
2166/2166 ———————————————————————————————————	19s	7ms/step	-	loss:	0.0068	-	mae:
2166/2166 —————	21s	7ms/step	-	loss:	0.0068	-	mae:
Epoch 71/200 2166/2166 ———————————————————————————————————	22s	7ms/step	_	loss:	0.0066	-	mae:
Epoch 72/200 2166/2166 ———————————————————————————————————	21s	8ms/step	_	loss:	0.0065	_	mae:
Epoch 73/200		8ms/step					
Epoch 74/200							
2166/2166	17s	8ms/step	-	loss:	0.0063	-	mae:

16s 7ms/step - loss: 0.0063 - mae: Epoch 76/200
195 7ms/step - loss: 0.0062 - mae: Epoch 77/200
Epoch 77/200 2166/2166
20s 7ms/step - loss: 0.0062 - mae: Epoch 78/200
Epoch 78/200 2166/2166
Epoch 79/200 2166/2166
165 7ms/step - loss: 0.0061 - mae: Epoch 80/200
Epoch 80/200 2166/2166
19s 7ms/step - loss: 0.0060 - mae: Epoch 81/200
Epoch 81/200 2166/2166 — 16s 7ms/step - loss: 0.0059 - mae: Epoch 82/200 2166/2166 — 19s 7ms/step - loss: 0.0059 - mae: Epoch 83/200 2166/2166 — 21s 7ms/step - loss: 0.0058 - mae: Epoch 84/200 2166/2166 — 20s 7ms/step - loss: 0.0058 - mae: Epoch 85/200 2166/2166 — 21s 7ms/step - loss: 0.0057 - mae: Epoch 86/200 2166/2166 — 21s 7ms/step - loss: 0.0057 - mae: Epoch 87/200 2166/2166 — 20s 7ms/step - loss: 0.0057 - mae: Epoch 88/200 2166/2166 — 20s 7ms/step - loss: 0.0055 - mae: Epoch 89/200 2166/2166 — 20s 7ms/step - loss: 0.0055 - mae: Epoch 90/200 2166/2166 — 20s 7ms/step - loss: 0.0054 - mae: Epoch 90/200 2166/2166 — 21s 7ms/step - loss: 0.0054 - mae: Epoch 91/200 2166/2166 — 22s 8ms/step - loss: 0.0053 - mae: Epoch 92/200
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21s 7ms/step - loss: 0.0058 - mae:
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Epoch 93/200 2166/2166 — 20s 7ms/step - loss: 0.0052 - mae:
Epoch 94/200
2166/2166 — 21s 7ms/step - loss: 0.0053 - mae:
Epoch 95/200
2166/2166 — 16s 7ms/step - loss: 0.0052 - mae: Epoch 96/200
2166/2166 — 20s 7ms/step - loss: 0.0051 - mae:
Epoch 97/200
2166/2166 21s 7ms/step - loss: 0.0051 - mae:
Epoch 98/200 2166/2166 — 20s 7ms/step - loss: 0.0050 - mae:
Epoch 99/200
2166/2166 — 15s 7ms/step - loss: 0.0051 - mae:
Epoch 100/200
2166/2166 — 16s 7ms/step - loss: 0.0050 - mae: Epoch 101/200
2166/2166 15s 7ms/step - loss: 0.0049 - mae:
Epoch 102/200
2166/2166 16s 7ms/step - loss: 0.0048 - mae:
Epoch 103/200 2166/2166 — 20s 7ms/step - loss: 0.0049 - mae:
Epoch 104/200
2166/2166 — 21s 7ms/step - loss: 0.0048 - mae:
Epoch 105/200
2166/2166 20s 7ms/step - loss: 0.0048 - mae: Epoch 106/200
2166/2166 — 21s 7ms/step - loss: 0.0048 - mae:
Epoch 107/200
2166/2166 21s 7ms/step - loss: 0.0046 - mae:
Epoch 108/200 2166/2166
2166/2166 20s 7ms/step - loss: 0.0047 - mae: Epoch 109/200
2166/2166 — 21s 7ms/step - loss: 0.0047 - mae:
Epoch 110/200
2166/2166 — 16s 7ms/step - loss: 0.0046 - mae:
Epoch 111/200 2166/2166 — 20s 7ms/step - loss: 0.0046 - mae:
Enoch 112/200

2166/2166	2166/2166	21.0	7ms/ston		10001	0 0045		maa.
175 8ms/step 10ss; 0.0046 mae;		215	/ms/step	_	1088:	0.0045	-	mae:
Epoch 114/200 2166/2166		17s	8ms/step	_	loss:	0.0046	_	mae:
Epoch 115/200 2166/2166	Epoch 114/200		·					
2166/2166		21s	8ms/step	-	loss:	0.0045	-	mae:
Epoch 116/200 2166/2166		226	Omc/ston		1000	0 0011		m20.
196 117 200 2166 218		225	ollis/step	_	1055.	0.0044	_	mae.
Epoch 117/200 2166/2166	2166/2166	19s	8ms/step	_	loss:	0.0044	_	mae:
Epoch 118/200 2166/2166	Epoch 117/200							
196 196 195 7ms/step 10ss: 0.0043 - mae: Epoch 119/200 2166/2166 21s 7ms/step 10ss: 0.0043 - mae: Epoch 120/200 2166/2166 20s 7ms/step 10ss: 0.0043 - mae: Epoch 121/200 2166/2166 16s 7ms/step 10ss: 0.0043 - mae: Epoch 121/200 2166/2166 16s 7ms/step 10ss: 0.0043 - mae: Epoch 122/200 2166/2166 16s 7ms/step 10ss: 0.0042 - mae: Epoch 123/200 2166/2166 21s 8ms/step 10ss: 0.0042 - mae: Epoch 124/200 2166/2166 20s 8ms/step 10ss: 0.0042 - mae: Epoch 126/200 2166/2166 15s 7ms/step 10ss: 0.0042 - mae: Epoch 126/200 2166/2166 21s 7ms/step 10ss: 0.0041 - mae: Epoch 126/200 2166/2166 22s 8ms/step 10ss: 0.0041 - mae: Epoch 128/200 2166/2166 20s 7ms/step 10ss: 0.0041 - mae: Epoch 139/200 2166/2166 21s 7ms/step 10ss: 0.0041 - mae: Epoch 131/200 2166/2166 21s 7ms/step 10ss: 0.0041 - mae: Epoch 131/200 2166/2166 21s 7ms/step 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 20s 7ms/step 10ss: 0.0040 - mae: Epoch 134/200 2166/2166 20s 7ms/step 10ss: 0.0040 - mae: Epoch 134/200 2166/2166 20s 7ms/step 10ss: 0.0040 - mae: Epoch 134/200 2166/2166 20s 7ms/step 10ss: 0.0040 - mae: Epoch 136/200 2166/2166 21s 7ms/step 10ss: 0.0040 - mae: Epoch 136/200 2166/2166 21s 7ms/step 10ss: 0.0039 - mae: Epoch 136/200 2166/2166 21s 7ms/step 10ss: 0.0039 - mae: Epoch 136/200 2166/2166 21s 7ms/step 10ss: 0.0039 - mae: Epoch 139/200 2166/2166 21s 7ms/step 10ss: 0.0039 - mae: Epoch 139/200 2166/2166 21s 7ms/step 10ss: 0.0039 - mae: Epoch 139/200 2166/2166 20s 7ms/step 10ss: 0.0039 - mae: Epoch 139/200 2166/2166 21s 7ms/step 10ss: 0.0039 - mae: Epoch 139/200 2166/2166 20s 7ms/step 10ss: 0.0039 - mae: Epoch 139/200		17s	8ms/step	-	loss:	0.0044	-	mae:
Epoch 119/200 2166/2166		19c	7mc/stan	_	1000	0 00/3	_	mae.
216 / 2166 215 7ms/step - 10ss: 0.0043 - mae: Epoch 120/200 2166/2166 20s 7ms/step - 10ss: 0.0043 - mae: Epoch 121/200 2166/2166 16s 7ms/step - 10ss: 0.0043 - mae: Epoch 122/200 2166/2166 16s 7ms/step - 10ss: 0.0042 - mae: Epoch 123/200 2166/2166 21s 8ms/step - 10ss: 0.0042 - mae: Epoch 124/200 2166/2166 20s 8ms/step - 10ss: 0.0042 - mae: Epoch 125/200 2166/2166 15s 7ms/step - 10ss: 0.0042 - mae: Epoch 126/200 2166/2166 15s 7ms/step - 10ss: 0.0041 - mae: Epoch 127/200 2166/2166 22s 8ms/step - 10ss: 0.0041 - mae: Epoch 128/200 2166/2166 20s 7ms/step - 10ss: 0.0041 - mae: Epoch 129/200 2166/2166 21s 7ms/step - 10ss: 0.0041 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0041 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 20s 7ms/step - 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 20s 7ms/step - 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 20s 7ms/step - 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 20s 7ms/step - 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0040 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0039 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0039 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0039 - mae: Epoch 131/200 2166/2166 21s 7ms/step - 10ss: 0.0039 - mae: Epoch 131/200 2166/2166 20s 7ms/step - 10ss: 0.0039 - mae: Epoch 140/200 2166/2166 21s 7ms/step - 10ss: 0.0039 - mae: Epoch 140/200 2166/2166 21s 7ms/step - 10ss: 0.0039 - mae: Epoch								
166/2166	2166/2166 —————	21s	7ms/step	_	loss:	0.0043	_	mae:
Epoch 121/200 2166/2166	Epoch 120/200				_			
166/2166		20s	7ms/step	-	loss:	0.0043	-	mae:
Epoch 122/200 2166/2166		16s	7ms/step	_	loss:	0.0043	_	mae:
Epoch 123/200 2166/2166	Epoch 122/200							
2166/2166		16s	7ms/step	-	loss:	0.0042	-	mae:
Epoch 124/200 2166/2166		21.0	Ome/ston		1000	0 0012		m20:
205 8ms/step - loss: 0.0042 - mae: Epoch 125/200		213	ollis/scep	_	1033.	0.0042	_	mae.
2166/2166		20s	8ms/step	_	loss:	0.0042	_	mae:
Epoch 126/200 2166/2166								
2166/2166		15s	7ms/step	-	loss:	0.0042	-	mae:
Epoch 127/200 2166/2166		15s	7ms/step	_	loss:	0.0041	_	mae:
Epoch 128/200 2166/2166	Epoch 127/200		·					
20s 7ms/step - loss: 0.0041 - mae: Epoch 129/200		22 s	8ms/step	-	loss:	0.0041	-	mae:
Epoch 129/200 2166/2166	2166/2166 ———————————————————————————————————	205	7ms/sten		1055.	0 0041	_	mae.
Epoch 130/200 2166/2166	Epoch 129/200							
2166/2166		15s	7ms/step	-	loss:	0.0041	-	mae:
The state of the	Epoch 130/200	21 c	7ms/stan	_	1000	0 00/1	_	mae.
Total Process		213	711137 3 CCP		1033.	0.0041		mac.
17s 8ms/step - loss: 0.0040 - mae: Epoch 133/200	-	16s	7ms/step	-	loss:	0.0040	-	mae:
20s 7ms/step - loss: 0.0040 - mae: Epoch 134/200 2166/2166 17s 8ms/step - loss: 0.0040 - mae: Epoch 135/200 2166/2166 19s 7ms/step - loss: 0.0040 - mae: Epoch 136/200 21s 7ms/step - loss: 0.0040 - mae: Epoch 136/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 137/200 2166/2166 21s 7ms/step - loss: 0.0039 - mae: Epoch 138/200 2166/2166 20s 7ms/step - loss: 0.0039 - mae: Epoch 139/200 2166/2166 21s 7ms/step - loss: 0.0039 - mae: Epoch 140/200 2166/2166 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 2166/2166 20s 7ms/step - loss: 0.0037 - mae: Epoch 141/200 2166/2166 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200 20s 7ms/st		176	Omc/ston		10001	0 0010		mao.
20s 7ms/step - loss: 0.0040 - mae: Epoch 134/200		1/3	ollis/scep	_	1055.	0.0040	_	mae.
17s 8ms/step - loss: 0.0040 - mae: Epoch 135/200 2166/2166 19s 7ms/step - loss: 0.0040 - mae: Epoch 136/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 137/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 138/200 2166/2166 20s 7ms/step - loss: 0.0039 - mae: Epoch 139/200 2166/2166 15s 7ms/step - loss: 0.0039 - mae: Epoch 140/200 2166/2166 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 21s 7ms/step - loss: 0.0037 - mae: Epoch 142/200 20s 7ms		20s	7ms/step	-	loss:	0.0040	-	mae:
Epoch 135/200 2166/2166 19s 7ms/step - loss: 0.0040 - mae: Epoch 136/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 137/200 15s 7ms/step - loss: 0.0039 - mae: Epoch 138/200 20s 7ms/step - loss: 0.0039 - mae: Epoch 139/200 15s 7ms/step - loss: 0.0039 - mae: Epoch 140/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200		17-	0		1	0.0040		
19s 7ms/step - loss: 0.0040 - mae: Epoch 136/200 2166/2166 21s 7ms/step - loss: 0.0039 - mae: Epoch 137/200 2166/2166 15s 7ms/step - loss: 0.0039 - mae: Epoch 138/200 2166/2166 20s 7ms/step - loss: 0.0039 - mae: Epoch 139/200 2166/2166 15s 7ms/step - loss: 0.0039 - mae: Epoch 140/200 2166/2166 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 2166/2166 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200 20s 7ms/step - loss: 0.0037 - mae:		1/5	øllis/step	-	1022:	0.0040	-	mae:
21s 7ms/step - loss: 0.0039 - mae: Epoch 137/200 2166/2166 — 15s 7ms/step - loss: 0.0039 - mae: Epoch 138/200 2166/2166 — 20s 7ms/step - loss: 0.0039 - mae: Epoch 139/200 2166/2166 — 15s 7ms/step - loss: 0.0039 - mae: Epoch 140/200 2166/2166 — 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 2166/2166 — 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200		19s	7ms/step	-	loss:	0.0040	-	mae:
Epoch 137/200 2166/2166			_ , .					
2166/2166 15s 7ms/step - loss: 0.0039 - mae: Epoch 138/200 20s 7ms/step - loss: 0.0039 - mae: Epoch 139/200 2166/2166 - loss: 0.0039 - mae: Epoch 140/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200		21s	/ms/step	-	loss:	0.0039	-	mae:
Epoch 138/200 2166/2166		15s	7ms/step	_	loss:	0.0039	_	mae:
Epoch 139/200 2166/2166			,					
2166/2166 15s 7ms/step - loss: 0.0039 - mae: Epoch 140/200 21s 7ms/step - loss: 0.0039 - mae: Epoch 141/200 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200 20s 7ms/step - loss: 0.0037 - mae:		20s	7ms/step	-	loss:	0.0039	-	mae:
Epoch 140/200 2166/2166		15s	7ms/sten	_	loss	a aa39	_	mae.
Epoch 141/200 2166/2166 — 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200	Epoch 140/200							
2166/2166 — 20s 7ms/step - loss: 0.0037 - mae: Epoch 142/200		21s	7ms/step	-	loss:	0.0039	-	mae:
Epoch 142/200		200	7ms/stan	_	1000	0 0037	_	mao.
2166/2166 15s 7ms/sten = loss: 0.0038 = mae:		203	/шз/зсер		1033.	0.0037		iliae .
, 10000 mac.	2166/2166 ————	15s	7ms/step	-	loss:	0.0038	-	mae:
Epoch 143/200 2166/2166 — 16s 7ms/step - loss: 0.0038 - mae:	Epoch 143/200	160	7ms/stan		10551	0 0020		mao.
Epoch 144/200		102	/ms/scep	_	1022:	0.0038	_	mae:
2166/2166 17s 8ms/step - loss: 0.0038 - mae:		17s	8ms/step	-	loss:	0.0038	-	mae:
Epoch 145/200	Epoch 145/200	4-	7 / :		1.	0.000=		
2166/2166 — 15s 7ms/step - loss: 0.0037 - mae: Epoch 146/200		15S	/ms/step	-	TOSS:	0.0037	-	mae:
2166/2166 — 16s 7ms/step - loss: 0.0037 - mae:		16s	7ms/step	_	loss:	0.0037	_	mae:
Epoch 147/200	Epoch 147/200		•					
2166/2166 — 16s 7ms/step - loss: 0.0037 - mae: Epoch 148/200		16s	/ms/step	-	Toss:	0.0037	-	mae:
2166/2166 — 15s 7ms/step - loss: 0.0037 - mae:		15s	7ms/step	_	loss:	0.0037	_	mae:
Epoch 149/200			1.					

2166/2166	16s	7ms/sten	_	lossi	0 0037	_	mae:
Epoch 150/200	103	7 III 3 / 3 CCP		1033.	0.0057		mac.
	20s	7ms/step	_	loss:	0.0036	-	mae:
Epoch 151/200							
2166/2166	22s	8ms/step	-	loss:	0.0037	-	mae:
Epoch 152/200 2166/2166 ———————————————————————————————————	165	7ms/sten	_	lossi	0 0037	_	mae.
Epoch 153/200	103	71113/3 ССР		1033.	0.0037		mac.
2166/2166	21s	8ms/step	_	loss:	0.0036	_	mae:
Epoch 154/200				_			
	16s	7ms/step	-	loss:	0.0036	-	mae:
Epoch 155/200 2166/2166 ———————————————————————————————————	16s	7ms/sten	_	loss:	0.0036	_	mae:
Epoch 156/200							
2166/2166	16s	7ms/step	-	loss:	0.0036	-	mae:
Epoch 157/200 2166/2166	200	7ms/ston		10001	0.0026		maa.
Epoch 158/200	205	/IIIS/Scep	-	1055.	0.0030	-	mae.
2166/2166	17s	8ms/step	_	loss:	0.0035	_	mae:
Epoch 159/200							
2166/2166 ———————————————————————————————————	16s	7ms/step	-	loss:	0.0035	-	mae:
Epoch 160/200 2166/2166 —	195	7ms/step	_	loss	0.0035	_	mae.
Epoch 161/200							
2166/2166 —	21s	7ms/step	-	loss:	0.0035	-	mae:
Epoch 162/200	20-	7		1	0 0035		
	205	7ms/step	-	1022:	0.0035	-	mae:
Epoch 163/200 2166/2166 ———————————————————————————————————	16s	7ms/step	_	loss:	0.0035	_	mae:
Epoch 164/200							
2166/2166 — Epoch 165/200	21s	7ms/step	-	loss:	0.0034	-	mae:
2166/2166	19s	7ms/step	_	loss:	0.0034	_	mae:
Epoch 166/200							
2166/2166 — Epoch 167/200	16s	7ms/step	-	loss:	0.0035	-	mae:
2166/2166	21s	7ms/step	_	loss:	0.0034	_	mae:
Epoch 168/200							
	20s	7ms/step	-	loss:	0.0034	-	mae:
Epoch 169/200 2166/2166 ———————————————————————————————————	21s	7ms/step	_	loss:	0.0034	_	mae:
Epoch 170/200							
	20s	7ms/step	-	loss:	0.0034	-	mae:
Epoch 171/200 2166/2166 ———————————————————————————————————	15c	7ms/step	_	1055.	0 0034	_	mae.
Epoch 172/200	100	/шэ/эсср		1033.	0.0054		mac.
	20s	7ms/step	-	loss:	0.0034	-	mae:
Epoch 173/200	22-	0		1	0.0034		
2166/2166 Epoch 174/200	225	8ms/step	_	1022:	0.0034	_	mae:
·	21s	8ms/step	-	loss:	0.0034	-	mae:
Epoch 175/200		_ , .					
2166/2166 — Epoch 176/200	205	7ms/step	-	TOSS:	0.0033	-	mae:
·	16s	7ms/step	_	loss:	0.0033	_	mae:
Epoch 177/200							
	21s	8ms/step	-	loss:	0.0033	-	mae:
Epoch 178/200 2166/2166 ———————————————————————————————————	16s	7ms/step	_	loss:	0.0033	_	mae:
Epoch 179/200							
2166/2166 —	16s	8ms/step	-	loss:	0.0033	-	mae:
Epoch 180/200 2166/2166 ———————————————————————————————————	165	2ms/sten	_	lossi	0 0032	_	mae.
Epoch 181/200	103	ошэ, эсср		1033.	0.0032		mac.
2166/2166	16s	7ms/step	-	loss:	0.0032	-	mae:
Epoch 182/200	15-	7mc/c+~~		1000	0 0022		mac:
2166/2166 Epoch 183/200	132	7ms/step	-	TO22:	⊎.⊎03Z	-	mae:
2166/2166 —	16s	7ms/step	-	loss:	0.0032	_	mae:
Epoch 184/200	20	7 / - !		1	0.0000		
2166/2166 — Epoch 185/200	205	7ms/step	-	TOSS:	0.0032	-	mae:
·	15s	7ms/step	_	loss:	0.0032	_	mae:
Epoch 186/200	<u> </u>	_					
	74	7		•			

2100/2100	215	/IIIS/Step	-	1022:	0.00 52	-	шае.
Epoch 187/200							
2166/2166 —————	21s	7ms/step	-	loss:	0.0032	-	mae:
Epoch 188/200							
2166/2166 —————	16s	8ms/step	_	loss:	0.0032	-	mae:
Epoch 189/200							
2166/2166 —————	21s	8ms/step	-	loss:	0.0032	-	mae:
Epoch 190/200							
2166/2166 —————	19s	7ms/step	-	loss:	0.0031	-	mae:
Epoch 191/200							
2166/2166 —————	21 s	8ms/step	-	loss:	0.0032	-	mae:
Epoch 192/200							
2166/2166 —————	21 s	8ms/step	_	loss:	0.0031	-	mae:
Epoch 193/200							
2166/2166 —————	15 s	7ms/step	-	loss:	0.0031	-	mae:
Epoch 194/200							
2166/2166 —	16s	8ms/step	-	loss:	0.0031	-	mae:
Epoch 195/200							
2166/2166 —————	17s	8ms/step	_	loss:	0.0031	-	mae:
Epoch 196/200							
2166/2166 —————	15s	7ms/step	_	loss:	0.0031	-	mae:
Epoch 197/200							
2166/2166 —————	21s	7ms/step	-	loss:	0.0031	-	mae:
Epoch 198/200							
2166/2166 —————	20s	7ms/step	-	loss:	0.0030	-	mae:
Epoch 199/200							
2166/2166 —————	20s	7ms/step	-	loss:	0.0031	-	mae:
Epoch 200/200							
2166/2166 —————	21 s	8ms/step	-	loss:	0.0031	-	mae:
	l ne	s Curve					
	LUS	3 Cui ve					
l ii					Train Los	s	
0.0200 -				_	Validatio	n l	oss
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1 mars						10	~
0.0125 -	M	mound	**	~~~	~~~~	4	
0.0100							
0.0100							

0.0075 -

0.0050

0.0025

```
# Make predictions
y_pred = model.predict(X_test)
# Convert back to original scale
y_test_actual = scaler.inverse_transform(np.column_stack([X_test[:, -1
y_pred_actual = scaler.inverse_transform(np.column_stack([X_test[:, -1
# Evaluate
from sklearn.metrics import mean_absolute_error, r2_score
mae = mean_absolute_error(y_test_actual, y_pred_actual)
r2 = r2_score(y_test_actual, y_pred_actual)
print(f"Mean Absolute Error: {mae:.4f}")
print(f"R2 Score: {r2:.4f}")
   542/542 -
                                 - 2s 4ms/step
     Mean Absolute Error: 1.2711
     R<sup>2</sup> Score: 0.5928
import numpy as np
import matplotlib.pyplot as plt
# Function to aggregate data into 5-minute intervals
def aggregate_to_5min(data, interval=120, method="mean"):
    data = data[: len(data) // interval * interval] # Trim to fit exact
    data = data.reshape(-1, interval) # Reshape into (num_intervals, intervals)
    if method == "mean":
        return data.mean(axis=1)
    elif method == "sum":
        return data.sum(axis=1)
# Aggregate actual and predicted values
y_train_actual_5min = aggregate_to_5min(y_train_actual)
y_train_pred_actual_5min = aggregate_to_5min(y_train_pred_actual)
y_test_actual_5min = aggregate_to_5min(y_test_actual)
y test pred actual 5min = aggregate to 5min(y test pred actual)
# Generate time axis (5-minute intervals)
time_train = np.arange(0, len(y_train_actual_5min) * 5, 5) # Every 5 mi
time_test = np.arange(len(y_train_actual_5min) * 5, (len(y_train_actual_
# Plot
plt.figure(figsize=(12, 6))
plt.plot(time train, y train actual 5min, label="Actual Data", color="b]
plt.plot(time_train, y_train_pred_actual_5min, label="Training Prediction")
plt.plot(time_test, y_test_pred_actual_5min, label="Testing Predictions"
plt.xlabel("Time (minutes)")
```