AAI_530_Final_Project

February 22, 2024

1 ParkEase:

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Class: AAI-530 Data Analytics and Internet of Things

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```
[]: # Import Libraries
import keras
import pandas as pd
import plotly.express as px
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
import os

from keras.models import Sequential, load_model
from keras.layers import LSTM, Dense, Dropout, Bidirectional, Activation,
SimpleRNN, GlobalAveragePooling1D, TimeDistributed
from keras.callbacks import ModelCheckpoint
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
print(f"Finished downloading {csv_file}, moving on")
```

aarhus_parking.csv already exists... continuing

1.0.1 Helper Functions

```
[]: # Function to create sequences and labels

def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)
```

```
1.0.2 EDA: Exploration Data Analysis
[]: # Peeking at the meta information from the dataset
    df.info(verbose = True)
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 55264 entries, 0 to 55263
    Data columns (total 6 columns):
        Column
                      Non-Null Count Dtype
    --- ----
                      _____
     0
        vehiclecount 55264 non-null int64
        updatetime 55264 non-null object
     2
                      55264 non-null int64
        id
        totalspaces 55264 non-null int64
        garagecode 55264 non-null object
         streamtime
                      55264 non-null object
    dtypes: int64(3), object(3)
    memory usage: 2.5+ MB
[]: print(f"Dataframe columns: {df.columns}")
    print(f"Dataframe length: {len(df)}")
    Dataframe columns: Index(['vehiclecount', 'updatetime', '_id', 'totalspaces',
    'garagecode',
           'streamtime'],
          dtype='object')
    Dataframe length: 55264
[]: # Check for NA values
    df.isna().sum()
[]: vehiclecount
    updatetime
                    0
    _id
                    0
    totalspaces
```

```
0
     streamtime
     dtype: int64
[]: # Check for null values
     df.isnull().sum()
[]: vehiclecount
                      0
     updatetime
                      0
                      0
     _id
     totalspaces
                      0
     garagecode
                      0
     streamtime
                      0
     dtype: int64
[]: # Taking a look at the first couple rows
     df.head(20)
                                                  _id
[]:
         vehiclecount
                                      updatetime
                                                        totalspaces
                                                                         garagecode \
     0
                        2014-05-22 09:09:04.145
                                                     1
                                                                  65
                                                                          NORREPORT
     1
                     0
                        2014-05-22 09:09:04.145
                                                     2
                                                                512
                                                                        SKOLEBAKKEN
     2
                  869
                        2014-05-22 09:09:04.145
                                                     3
                                                               1240
                                                                        SCANDCENTER
     3
                                                     4
                    22
                        2014-05-22 09:09:04.145
                                                                953
                                                                             BRUUNS
     4
                                                     5
                   124
                        2014-05-22 09:09:04.145
                                                                130
                                                                       BUSGADEHUSET
     5
                   106
                        2014-05-22 09:09:04.145
                                                     6
                                                                400
                                                                            MAGASIN
                                                     7
                                                                 210
     6
                   115
                        2014-05-22 09:09:04.145
                                                                      KALKVAERKSVEJ
     7
                   233
                        2014-05-22 09:09:04.145
                                                                 700
                                                                            SALLING
     8
                        2014-05-22 09:39:01.803
                                                     9
                                                                          NORREPORT
                                                                  65
     9
                        2014-05-22 09:39:01.803
                                                    10
                                                                512
                                                                        SKOLEBAKKEN
     10
                  959
                        2014-05-22 09:39:01.803
                                                    11
                                                               1240
                                                                        SCANDCENTER
     11
                    22
                        2014-05-22 09:39:01.803
                                                                953
                                                    12
                                                                             BRUUNS
                                                                       BUSGADEHUSET
     12
                   124
                        2014-05-22 09:39:01.803
                                                    13
                                                                 130
     13
                   119
                        2014-05-22 09:39:01.803
                                                    14
                                                                 400
                                                                            MAGASIN
     14
                   121
                        2014-05-22 09:39:01.803
                                                    15
                                                                 210
                                                                      KALKVAERKSVEJ
     15
                   282
                        2014-05-22 09:39:01.803
                                                    16
                                                                700
                                                                            SALLING
                        2014-05-22 10:10:51.543
     16
                                                    17
                                                                  65
                                                                          NORREPORT
     17
                     0
                        2014-05-22 10:10:51.543
                                                    18
                                                                512
                                                                        SKOLEBAKKEN
     18
                  1014
                        2014-05-22 10:10:51.543
                                                    19
                                                               1240
                                                                        SCANDCENTER
                        2014-05-22 10:10:51.543
                                                    20
                                                                953
     19
                    22
                                                                             BRUUNS
                   streamtime
     0
         2014-11-03 16:18:44
     1
         2014-11-03 16:18:44
     2
         2014-11-03 16:18:44
     3
         2014-11-03 16:18:44
     4
         2014-11-03 16:18:44
```

garagecode

5

2014-11-03 16:18:44

0

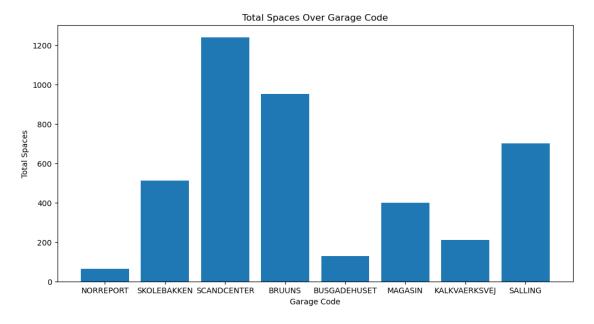
```
6
        2014-11-03 16:18:44
     7
        2014-11-03 16:18:44
     8
        2014-11-03 16:18:44
        2014-11-03 16:18:44
     10 2014-11-03 16:18:44
     11 2014-11-03 16:18:44
     12 2014-11-03 16:18:44
     13 2014-11-03 16:18:44
     14 2014-11-03 16:18:44
     15 2014-11-03 16:18:44
     16 2014-11-03 16:18:44
     17 2014-11-03 16:18:44
     18 2014-11-03 16:18:44
     19 2014-11-03 16:18:44
[]: # Checking for valid garage codes + unique codes
     total_gcodes = len(df.garagecode)
     total unique gcodes = len(df.garagecode.unique())
     print(f"Unique garage codes", df.garagecode.unique())
     print(f"There are {total_gcodes} total garage codes")
     print(f"There are {total_unique_gcodes} unique garage codes")
    Unique garage codes ['NORREPORT' 'SKOLEBAKKEN' 'SCANDCENTER' 'BRUUNS'
    'BUSGADEHUSET' 'MAGASIN'
     'KALKVAERKSVEJ' 'SALLING']
    There are 55264 total garage codes
    There are 8 unique garage codes
[]: # Visualize + Check for any uneven distribution
     value_count = df.garagecode.value_counts()
     df_count = pd.DataFrame({'GarageCode': value_count.index, 'Ammount':__
     ⇒value count.values})
     fig = px.bar(df_count, x='GarageCode', y = 'Ammount', title="Unique Garage_
      ⇔Codes", color='GarageCode')
     fig.show()
```

Conclusions 1

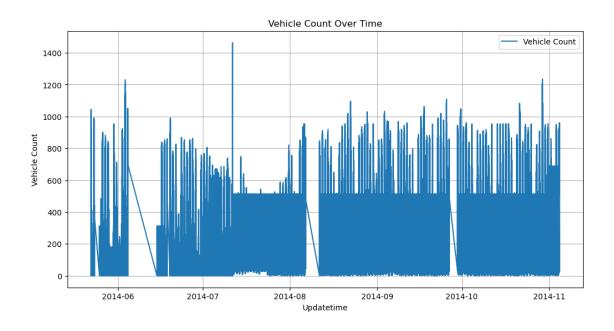
- We have **55264** entries in the dataset
- At the first glance the date seems clean and well organized
- Each entry provides all of the attributes
- Next, we will need to check the data quality and if there are any issues with the data itself
- Let's convert updatetime and streamtime to the pd.datetime format

```
[]: # Convert 'streamtime' column to datetime
df['streamtime'] = pd.to_datetime(df['streamtime'], format='%Y-%m-%d %H:%M:%S')
# Convert 'updatetime' column to datetime
df['updatetime'] = pd.to_datetime(df['updatetime'], format='mixed')
```

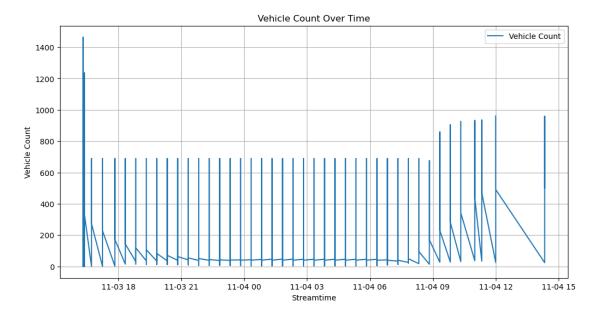
```
[]: # Bar chart for 'totalspaces' over 'garagecode' use plt
plt.figure(figsize=(12, 6))
plt.bar(df['garagecode'], df['totalspaces'])
plt.title('Total Spaces Over Garage Code')
plt.xlabel('Garage Code')
plt.ylabel('Total Spaces')
plt.show()
```



```
[]: # Line plot of 'vehiclecount' over 'updatetime'
plt.figure(figsize=(12, 6))
plt.plot(df['updatetime'], df['vehiclecount'], label='Vehicle Count')
plt.title('Vehicle Count Over Time')
plt.xlabel('Updatetime')
plt.ylabel('Vehicle Count')
plt.legend()
plt.grid(True)
plt.show()
```



```
[]: # Line plot of 'vehiclecount' over 'streamtime'
plt.figure(figsize=(12, 6))
plt.plot(df['streamtime'], df['vehiclecount'], label='Vehicle Count')
plt.title('Vehicle Count Over Time')
plt.xlabel('Streamtime')
plt.ylabel('Vehicle Count')
plt.legend()
plt.grid(True)
plt.show()
```



Conclusions 2

- From the dataset description the difference between streamline and updatetime was not clear.
- From the plots above we can see that we have more updatetime datapoints compared to the streamtime.
- Let's check the difference between streamtime and updatetime.

```
[]: # Get unique streamtime values
     unique_streamtime_values = df['streamtime'].unique()
     print(f"Unique streamtime values: {unique_streamtime_values}")
     print(f"Unique streamtime values length: {len(unique_streamtime_values)}")
    Unique streamtime values: <DatetimeArray>
    ['2014-11-03 16:18:44', '2014-11-03 16:19:11', '2014-11-03 16:19:40',
     '2014-11-03 16:20:08', '2014-11-03 16:22:16', '2014-11-03 16:22:34',
     '2014-11-03 16:23:01', '2014-11-03 16:43:16', '2014-11-03 17:14:47',
     '2014-11-03 17:50:09', '2014-11-03 18:20:01', '2014-11-03 18:50:01',
     '2014-11-03 19:20:02', '2014-11-03 19:50:02', '2014-11-03 20:20:01',
     '2014-11-03 20:50:01', '2014-11-03 21:20:02', '2014-11-03 21:50:01',
     '2014-11-03 22:20:02', '2014-11-03 22:50:01', '2014-11-03 23:20:02',
     '2014-11-03 23:50:02', '2014-11-04 00:20:02', '2014-11-04 00:50:02',
     '2014-11-04 01:20:01', '2014-11-04 01:50:01', '2014-11-04 02:20:01',
     '2014-11-04 02:50:02', '2014-11-04 03:20:01', '2014-11-04 03:50:01',
     '2014-11-04 04:20:02', '2014-11-04 04:50:04', '2014-11-04 05:20:01',
     '2014-11-04 05:50:02', '2014-11-04 06:20:02', '2014-11-04 06:50:01',
     '2014-11-04 07:20:01', '2014-11-04 07:50:01', '2014-11-04 08:20:02',
     '2014-11-04 08:50:01', '2014-11-04 09:20:03', '2014-11-04 09:50:02',
     '2014-11-04 10:20:03', '2014-11-04 11:00:02', '2014-11-04 11:20:03',
     '2014-11-04 12:00:01', '2014-11-04 14:20:03']
    Length: 47, dtype: datetime64[ns]
    Unique streamtime values length: 47
[]: # Get the minimum 'streamtime'
     min_streamtime = df['streamtime'].min()
     # Get the maximum 'streamtime'
     max_streamtime = df['streamtime'].max()
     print(f"Minimum Streamtime: {min_streamtime}")
     print(f"Maximum Streamtime: {max_streamtime}")
    Minimum Streamtime: 2014-11-03 16:18:44
    Maximum Streamtime: 2014-11-04 14:20:03
[]: # Get the minimum 'updatetime'
     min updatetime = df['updatetime'].min()
```

```
# Get the maximum 'updatetime'
max_updatetime = df['updatetime'].max()

print(f"Minimum Update time: {min_updatetime}")
print(f"Maximum Update time: {max_updatetime}")
```

Minimum Update time: 2014-05-22 09:09:04.145000 Maximum Update time: 2014-11-04 14:13:47.581000

Conclusions 3

- Streamtime ranges between 2 dates 2014-11-03 and 2014-11-04
- These were the dates when the data uploaded to the server
- Updatetime ranges between dates 2014-05-22 and 2014-11-04
- These were the date times when the parking garages reported on the vehcile counts
- We are interested in predictions based in the updatetime, and will not be using streamtime
- From the plot of vehcilecount over the updatetime, it seemed that we had some missing dates in our data set. Let's explore.

```
[]: # Find the minimum and maximum timestamps
     min_timestamp = df['updatetime'].dt.date.min()
     max_timestamp = df['updatetime'].dt.date.max()
     # Generate a date range from the minimum to the maximum timestamp
     expected_dates = pd.date_range(start=min_timestamp, end=max_timestamp, freq='D')
     actual_dates = pd.to_datetime(df['updatetime'].dt.date.unique())
     # Check for missing timestamps
     missing_timestamps = expected_dates[~expected_dates.isin(actual_dates)]
     missing_timestamps_df = pd.DataFrame(missing_timestamps,__
      ⇔columns=['missing_timestamps'])
     if missing_timestamps.empty:
         print("No missing timestamps found.")
     else:
         print("Missing timestamps found:")
         display(missing_timestamps_df.head(100))
         print(f"Total missing timestamps: {len(missing timestamps)}")
```

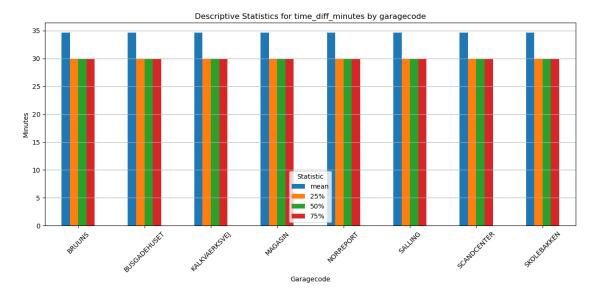
Missing timestamps found:

```
missing_timestamps
0 2014-05-24
1 2014-06-05
2 2014-06-06
```

```
3
               2014-06-07
    4
               2014-06-08
    5
               2014-06-09
    6
               2014-06-10
    7
               2014-06-11
    8
               2014-06-12
    9
               2014-06-13
    10
               2014-08-07
    11
               2014-08-08
               2014-08-09
    12
    13
               2014-08-10
    14
               2014-09-27
    15
               2014-09-28
    Total missing timestamps: 16
[]: # Check the frequency of the reporting
     df_diff = df.copy()
     # Sort by garagecode and updatetime
     df_diff = df_diff.sort_values(['garagecode', 'updatetime'])
     # Calculate the time difference for each garagecode
     df_diff['time_diff_minutes'] = df_diff.groupby('garagecode')['updatetime'].
      ⇒diff() / pd.Timedelta(minutes=1)
     # Plot descriptive statistics for time diff_minutes for each garagecode_
      \hookrightarrow separately
     garagecode_groups = df_diff.groupby('garagecode')['time_diff_minutes']
     garagecode_stats = garagecode_groups.describe()
     display(garagecode_stats)
     # Plot boxplots
     garagecode_stats[['mean', '25%', '50%', '75%']].plot(kind='bar', figsize=(12, ____
      ⇔6))
     plt.ylabel('Minutes')
     plt.xlabel('Garagecode')
     plt.title('Descriptive Statistics for time_diff_minutes by garagecode')
     plt.xticks(rotation=45)
     plt.legend(title='Statistic')
     plt.grid(axis='y')
     plt.tight_layout()
     plt.show()
                                                                  25%
                     count
                                 mean
                                               std
                                                         min
                                                                        50% \
    garagecode
    BRUUNS
                   6907.0 34.652486 205.318242 0.000033
                                                              29.9999
                                                                       30.0
```

6907.0	34.652486	205.318242	0.000033	29.9999	30.0
6907.0	34.652486	205.318242	0.000033	29.9999	30.0
6907.0	34.652486	205.318242	0.000033	29.9999	30.0
6907.0	34.652486	205.318242	0.000033	29.9999	30.0
6907.0	34.652486	205.318242	0.000033	29.9999	30.0
6907.0	34.652486	205.318242	0.000033	29.9999	30.0
6907.0	34.652486	205.318242	0.000033	29.9999	30.0
	6907.0 6907.0 6907.0 6907.0 6907.0	6907.0 34.652486 6907.0 34.652486 6907.0 34.652486 6907.0 34.652486 6907.0 34.652486	6907.0 34.652486 205.318242 6907.0 34.652486 205.318242 6907.0 34.652486 205.318242 6907.0 34.652486 205.318242 6907.0 34.652486 205.318242	6907.0 34.652486 205.318242 0.000033 6907.0 34.652486 205.318242 0.000033 6907.0 34.652486 205.318242 0.000033 6907.0 34.652486 205.318242 0.000033 6907.0 34.652486 205.318242 0.000033 6907.0 34.652486 205.318242 0.000033	6907.0 34.652486 205.318242 0.000033 29.9999 6907.0 34.652486 205.318242 0.000033 29.9999 6907.0 34.652486 205.318242 0.000033 29.9999 6907.0 34.652486 205.318242 0.000033 29.9999 6907.0 34.652486 205.318242 0.000033 29.9999 6907.0 34.652486 205.318242 0.000033 29.9999

	75%	max
garagecode		
BRUUNS	30.0001	14747.039983
BUSGADEHUSET	30.0001	14747.039983
KALKVAERKSVEJ	30.0001	14747.039983
MAGASIN	30.0001	14747.039983
NORREPORT	30.0001	14747.039983
SALLING	30.0001	14747.039983
SCANDCENTER	30.0001	14747.039983
SKOLEBAKKEN	30.0001	14747.039983



Conclusions 4

- $\bullet~$ We have total of ${\bf 16}~{\bf dates}$ missing from the dataset.
- For each garage most of the data is reported with the difference of **30 minutes**
- Let's also investigate what data was reported per each garage.

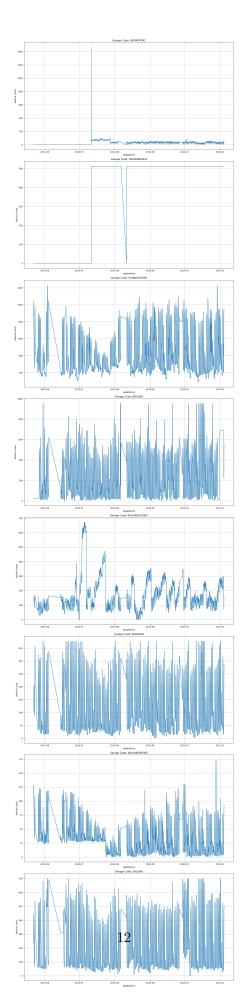
```
[]: garage_codes = df['garagecode'].unique()

# Create subplots
fig, axes = plt.subplots(len(garage_codes), figsize=(15, 8*len(garage_codes)))
```

```
# Iterate through each garage code
for i, code in enumerate(garage_codes):
    # Filter dataframe for current garage code
    sub_df = df[df['garagecode'] == code]

# Plot vehicle count against timestamp
    axes[i].plot(sub_df['updatetime'], sub_df['vehiclecount'])
    axes[i].set_title(f'Garage Code: {code}')
    axes[i].set_xlabel('Updatetime')
    axes[i].set_ylabel('Vehicle Count')
    axes[i].grid(True)

plt.tight_layout()
plt.show()
```



1.0.3 Conclusions - EDA and Data Quality

- We have **55264** entries in the dataset
- There is total of 16 missing dates when no vehiclecount was reported. This amounts to ≈ 768 missing entries, since for every day the data is reported every 30 minutes.
- Looks like June and August and September have missing entries. Those missing entries are consistent across oll of the garage codes.
- Additionally, it seems there might be data quality issues per garage level:
 - SKOLEBAKKEN was probably used for a company's vehicles parking or similar, since vehicle count did not change across multiple days
 - NORREPORT has 0 cars parked up to mid July, then an outlier day with 1400 parked, following days with under 200 cars parked
 - KALKVAERKSVEJ up to mid July KALKVAERKSVEJ always had at least 25 cars parked permanently
 - Data for the remaining garages SCANDCENTER, BRUUNS, BUSGADEHUSET and MAGASIN and SALLING looks to be in a good shape, besides the 16 missing dates

1.0.4 Preprocessing the Dataset

Given the conclusion above, we decided to do the following preprocessing steps:

- Normalize data to increase model performance and prevent issues, such as gradient explosion and vanishing
- We will not be backfilling missing dates, since this will result in a loss of a temporal pattern, instead we will focus on efficiently using the existing data
- Every garage has slightly different patterns of occupancy depending on the date / time. From our predict perspective it makes sense to provide a Garage level APIs, thus we will be training models for each garage separately

```
[]: # Normalize the dataset
scaler = MinMaxScaler(feature_range=(0, 1))
```

1.0.5 Creating the LSTM Model

```
# Create sequences and labels
  X, y = create_sequences(occupancy_scaled, sequence_length)
  # Split data into training and testing sets
  →random_state=42, shuffle=False)
  # Define the LSTM model
  model = Sequential()
  model.
→add(Bidirectional(LSTM(64,input_shape=(sequence_length,1),return_sequences=True)))
  model.add(Dropout(0.2))
  model.add(Bidirectional(LSTM(32, return_sequences=True)))
  model.add(Dropout(0.2))
  model.add(Bidirectional(LSTM(16)))
  model.add(Dropout(0.2))
  model.add(Dense(64,activation='linear'))
  model.add(Dropout(0.5))
  model.add(Dense(32,activation='relu'))
  model.add(Dropout(0.5))
  model.add(Dense(1))
  model.add(Activation('linear'))
  # Model Path
  model_path = "model_lstm.h5"
  # Compile the model
  model.compile(optimizer='adam', loss='mean_squared_error')
  # Train the model
  history = model.fit(X_train, y_train, epochs=20, batch_size=32,__
→validation_split=0.05, verbose=2,
                  callbacks = [keras.callbacks.
⇒EarlyStopping(monitor='val_loss', min_delta=0, patience=10, verbose=0, __

mode='min'),
                  keras.callbacks.
→ModelCheckpoint(model_path,monitor='val_loss', save_best_only=True, __
⇒mode='min', verbose=0)])
  # Evaluate the model
  train_loss = model.evaluate(X_train, y_train, verbose=0)
  test_loss = model.evaluate(X_test, y_test, verbose=0)
  # Predict occupancy values on testing set
  y_test_pred = model.predict(X_test)
```

```
# Inverse transform the predicted and actual values to their original scale
y_test = scaler.inverse_transform(y_test.reshape(-1, 1)).flatten()
y_test_pred = scaler.inverse_transform(y_test_pred.reshape(-1, 1)).flatten()

# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, y_test_pred)

# Store results in the dictionary
results[area_id] = {
    'train_loss': train_loss,
    'test_loss': test_loss,
    'mae': mae,
    'loss': history.history['loss'],
    'val_loss': history.history['val_loss'],
    'y_test_pred': y_test_pred,
    'y_test': y_test
}
```

Epoch 1/20 164/164 - 21s - loss: 0.0151 - val_loss: 0.0073 - 21s/epoch - 129ms/step Epoch 2/20

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 0.0057 - val_loss: 0.0099 - 7s/epoch - 40ms/step
Epoch 3/20
164/164 - 6s - loss: 0.0211 - val_loss: 0.0081 - 6s/epoch - 38ms/step
Epoch 4/20
164/164 - 6s - loss: 0.0071 - val_loss: 0.0214 - 6s/epoch - 37ms/step
Epoch 5/20
164/164 - 6s - loss: 0.0062 - val_loss: 0.0176 - 6s/epoch - 38ms/step
Epoch 6/20
164/164 - 7s - loss: 0.0159 - val_loss: 0.0181 - 7s/epoch - 40ms/step
Epoch 7/20
164/164 - 6s - loss: 0.0186 - val loss: 0.0362 - 6s/epoch - 37ms/step
Epoch 8/20
164/164 - 6s - loss: 0.0187 - val loss: 0.0398 - 6s/epoch - 38ms/step
Epoch 9/20
164/164 - 6s - loss: 0.0374 - val loss: 0.0433 - 6s/epoch - 38ms/step
Epoch 10/20
164/164 - 6s - loss: 0.0430 - val_loss: 0.0119 - 6s/epoch - 37ms/step
Epoch 11/20
164/164 - 6s - loss: 0.0132 - val_loss: 0.0361 - 6s/epoch - 36ms/step
```

```
44/44 [=======] - 2s 26ms/step
Epoch 1/20
164/164 - 17s - loss: 0.0070 - val_loss: 0.0016 - 17s/epoch - 104ms/step
Epoch 2/20
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/keras/src/engine/training.py:3103: UserWarning:
You are saving your model as an HDF5 file via `model.save()`. This file format
is considered legacy. We recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
164/164 - 7s - loss: 0.0029 - val_loss: 0.0021 - 7s/epoch - 41ms/step
Epoch 3/20
164/164 - 6s - loss: 0.0023 - val_loss: 0.0013 - 6s/epoch - 38ms/step
Epoch 4/20
164/164 - 6s - loss: 0.0023 - val_loss: 8.6806e-04 - 6s/epoch - 38ms/step
Epoch 5/20
164/164 - 6s - loss: 0.0019 - val_loss: 7.5070e-04 - 6s/epoch - 37ms/step
Epoch 6/20
164/164 - 6s - loss: 0.0016 - val_loss: 0.0010 - 6s/epoch - 38ms/step
Epoch 7/20
164/164 - 6s - loss: 0.0018 - val_loss: 9.3426e-04 - 6s/epoch - 39ms/step
Epoch 8/20
164/164 - 6s - loss: 0.0017 - val_loss: 0.0013 - 6s/epoch - 37ms/step
Epoch 9/20
164/164 - 6s - loss: 0.0016 - val loss: 0.0015 - 6s/epoch - 37ms/step
Epoch 10/20
164/164 - 6s - loss: 0.0016 - val loss: 0.0015 - 6s/epoch - 39ms/step
Epoch 11/20
164/164 - 6s - loss: 0.0018 - val loss: 0.0020 - 6s/epoch - 38ms/step
Epoch 12/20
164/164 - 6s - loss: 0.0016 - val_loss: 8.4152e-04 - 6s/epoch - 38ms/step
Epoch 13/20
164/164 - 7s - loss: 0.0014 - val loss: 0.0013 - 7s/epoch - 40ms/step
Epoch 14/20
164/164 - 6s - loss: 0.0012 - val_loss: 0.0017 - 6s/epoch - 37ms/step
Epoch 15/20
164/164 - 6s - loss: 0.0012 - val_loss: 0.0012 - 6s/epoch - 37ms/step
44/44 [========] - 2s 24ms/step
Epoch 1/20
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

Epoch 2/20

You are saving your model as an HDF5 file via `model.save()`. This file format

164/164 - 19s - loss: 0.0093 - val_loss: 0.0043 - 19s/epoch - 114ms/step

is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.

```
164/164 - 7s - loss: 0.0041 - val_loss: 0.0040 - 7s/epoch - 45ms/step
Epoch 3/20
164/164 - 6s - loss: 0.0050 - val_loss: 0.0077 - 6s/epoch - 39ms/step
Epoch 4/20
164/164 - 6s - loss: 0.0075 - val_loss: 0.0060 - 6s/epoch - 37ms/step
Epoch 5/20
164/164 - 6s - loss: 0.0047 - val_loss: 0.0072 - 6s/epoch - 37ms/step
Epoch 6/20
164/164 - 6s - loss: 0.0031 - val_loss: 0.0075 - 6s/epoch - 37ms/step
Epoch 7/20
164/164 - 7s - loss: 0.0025 - val_loss: 0.0031 - 7s/epoch - 41ms/step
Epoch 8/20
164/164 - 6s - loss: 0.0028 - val loss: 0.0028 - 6s/epoch - 38ms/step
Epoch 9/20
164/164 - 6s - loss: 0.0039 - val_loss: 0.0055 - 6s/epoch - 38ms/step
Epoch 10/20
164/164 - 6s - loss: 0.0153 - val_loss: 0.0089 - 6s/epoch - 36ms/step
Epoch 11/20
164/164 - 6s - loss: 0.0116 - val_loss: 0.0119 - 6s/epoch - 38ms/step
Epoch 12/20
164/164 - 6s - loss: 0.0082 - val loss: 0.0138 - 6s/epoch - 38ms/step
Epoch 13/20
164/164 - 6s - loss: 0.0074 - val loss: 0.0039 - 6s/epoch - 39ms/step
Epoch 14/20
164/164 - 6s - loss: 0.0067 - val loss: 0.0029 - 6s/epoch - 36ms/step
Epoch 15/20
164/164 - 7s - loss: 0.0178 - val_loss: 0.0136 - 7s/epoch - 40ms/step
Epoch 16/20
164/164 - 8s - loss: 0.0145 - val_loss: 0.0251 - 8s/epoch - 47ms/step
Epoch 17/20
164/164 - 6s - loss: 0.0097 - val_loss: 0.0053 - 6s/epoch - 36ms/step
Epoch 18/20
164/164 - 6s - loss: 0.0104 - val_loss: 0.0062 - 6s/epoch - 37ms/step
44/44 [========] - 3s 24ms/step
Epoch 1/20
164/164 - 22s - loss: 0.0198 - val_loss: 0.0038 - 22s/epoch - 133ms/step
Epoch 2/20
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 0.0069 - val_loss: 0.0067 - 7s/epoch - 42ms/step
Epoch 3/20
164/164 - 6s - loss: 0.0072 - val_loss: 0.0047 - 6s/epoch - 39ms/step
Epoch 4/20
164/164 - 6s - loss: 0.0151 - val loss: 0.0443 - 6s/epoch - 39ms/step
Epoch 5/20
164/164 - 6s - loss: 0.0306 - val loss: 0.0088 - 6s/epoch - 38ms/step
Epoch 6/20
164/164 - 6s - loss: 0.0067 - val_loss: 0.0948 - 6s/epoch - 38ms/step
Epoch 7/20
164/164 - 6s - loss: 0.0168 - val loss: 0.2988 - 6s/epoch - 37ms/step
Epoch 8/20
164/164 - 6s - loss: 0.0250 - val_loss: 0.1914 - 6s/epoch - 37ms/step
Epoch 9/20
164/164 - 6s - loss: 0.0215 - val_loss: 0.0039 - 6s/epoch - 37ms/step
Epoch 10/20
164/164 - 6s - loss: 0.0142 - val_loss: 0.0720 - 6s/epoch - 38ms/step
Epoch 11/20
164/164 - 6s - loss: 0.0112 - val_loss: 0.0847 - 6s/epoch - 37ms/step
44/44 [========= ] - 3s 29ms/step
Epoch 1/20
164/164 - 31s - loss: 0.0010 - val_loss: 0.0042 - 31s/epoch - 186ms/step
Epoch 2/20
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 6.6901e-04 - val_loss: 0.0021 - 7s/epoch - 41ms/step
Epoch 3/20
164/164 - 6s - loss: 0.0013 - val_loss: 0.0123 - 6s/epoch - 39ms/step
Epoch 4/20
164/164 - 6s - loss: 7.1890e-04 - val_loss: 0.0056 - 6s/epoch - 39ms/step
Epoch 5/20
164/164 - 6s - loss: 4.0186e-04 - val_loss: 0.0093 - 6s/epoch - 37ms/step
Epoch 6/20
164/164 - 6s - loss: 3.7431e-04 - val_loss: 0.0050 - 6s/epoch - 38ms/step
Epoch 7/20
164/164 - 6s - loss: 9.7034e-04 - val loss: 0.0035 - 6s/epoch - 37ms/step
Epoch 8/20
164/164 - 6s - loss: 8.5882e-04 - val loss: 0.0033 - 6s/epoch - 37ms/step
Epoch 9/20
164/164 - 7s - loss: 4.3762e-04 - val loss: 0.0077 - 7s/epoch - 43ms/step
Epoch 10/20
164/164 - 6s - loss: 3.1008e-04 - val loss: 0.0076 - 6s/epoch - 38ms/step
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 0.0078 - val_loss: 0.0255 - 7s/epoch - 43ms/step
Epoch 3/20
164/164 - 8s - loss: 0.0111 - val_loss: 0.0277 - 8s/epoch - 47ms/step
Epoch 4/20
164/164 - 9s - loss: 0.0066 - val_loss: 0.0155 - 9s/epoch - 54ms/step
Epoch 5/20
164/164 - 12s - loss: 0.0087 - val_loss: 0.0344 - 12s/epoch - 76ms/step
Epoch 6/20
164/164 - 8s - loss: 0.0130 - val_loss: 0.0114 - 8s/epoch - 47ms/step
Epoch 7/20
164/164 - 7s - loss: 0.0166 - val_loss: 0.0078 - 7s/epoch - 41ms/step
Epoch 8/20
164/164 - 7s - loss: 0.0139 - val_loss: 0.0087 - 7s/epoch - 40ms/step
Epoch 9/20
164/164 - 8s - loss: 0.0105 - val_loss: 0.0181 - 8s/epoch - 47ms/step
Epoch 10/20
164/164 - 7s - loss: 0.0142 - val loss: 0.0238 - 7s/epoch - 45ms/step
Epoch 11/20
164/164 - 7s - loss: 0.0209 - val loss: 0.0334 - 7s/epoch - 42ms/step
Epoch 12/20
164/164 - 8s - loss: 0.0137 - val_loss: 0.0144 - 8s/epoch - 48ms/step
Epoch 13/20
164/164 - 7s - loss: 0.0041 - val_loss: 0.0134 - 7s/epoch - 42ms/step
Epoch 14/20
164/164 - 7s - loss: 0.0036 - val_loss: 0.0151 - 7s/epoch - 42ms/step
Epoch 15/20
164/164 - 6s - loss: 0.0054 - val_loss: 0.0132 - 6s/epoch - 39ms/step
Epoch 16/20
164/164 - 6s - loss: 0.0094 - val_loss: 0.0274 - 6s/epoch - 39ms/step
Epoch 17/20
164/164 - 6s - loss: 0.0113 - val_loss: 0.0104 - 6s/epoch - 37ms/step
44/44 [========] - 11s 136ms/step
```

```
Epoch 1/20
164/164 - 28s - loss: 0.0226 - val_loss: 0.0052 - 28s/epoch - 172ms/step
Epoch 2/20
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 0.0163 - val loss: 0.0109 - 7s/epoch - 43ms/step
Epoch 3/20
164/164 - 7s - loss: 0.0193 - val_loss: 0.0066 - 7s/epoch - 42ms/step
Epoch 4/20
164/164 - 8s - loss: 0.0129 - val loss: 0.0075 - 8s/epoch - 50ms/step
Epoch 5/20
164/164 - 6s - loss: 0.0141 - val loss: 0.0138 - 6s/epoch - 37ms/step
Epoch 6/20
164/164 - 6s - loss: 0.0701 - val_loss: 0.0168 - 6s/epoch - 36ms/step
Epoch 7/20
164/164 - 6s - loss: 0.0171 - val_loss: 0.0184 - 6s/epoch - 38ms/step
Epoch 8/20
164/164 - 7s - loss: 0.0229 - val_loss: 0.0049 - 7s/epoch - 43ms/step
Epoch 9/20
164/164 - 6s - loss: 0.0085 - val loss: 0.0031 - 6s/epoch - 38ms/step
Epoch 10/20
164/164 - 6s - loss: 0.0060 - val_loss: 0.0175 - 6s/epoch - 38ms/step
Epoch 11/20
164/164 - 7s - loss: 0.0058 - val_loss: 0.0210 - 7s/epoch - 41ms/step
Epoch 12/20
164/164 - 6s - loss: 0.0190 - val_loss: 0.0600 - 6s/epoch - 36ms/step
Epoch 13/20
164/164 - 6s - loss: 0.0236 - val_loss: 0.0512 - 6s/epoch - 37ms/step
Epoch 14/20
164/164 - 6s - loss: 0.0500 - val_loss: 0.0350 - 6s/epoch - 38ms/step
Epoch 15/20
164/164 - 6s - loss: 0.0324 - val_loss: 0.0444 - 6s/epoch - 38ms/step
Epoch 16/20
164/164 - 6s - loss: 0.0262 - val_loss: 0.0034 - 6s/epoch - 39ms/step
Epoch 17/20
164/164 - 6s - loss: 0.0294 - val loss: 0.0174 - 6s/epoch - 36ms/step
Epoch 18/20
164/164 - 6s - loss: 0.0227 - val_loss: 0.0200 - 6s/epoch - 37ms/step
Epoch 19/20
164/164 - 6s - loss: 0.0183 - val_loss: 0.0157 - 6s/epoch - 36ms/step
44/44 [========] - 4s 39ms/step
Epoch 1/20
```

```
164/164 - 25s - loss: 0.0309 - val_loss: 3.1643e-04 - 25s/epoch - 153ms/step Epoch 2/20
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 0.0015 - val loss: 0.0011 - 7s/epoch - 42ms/step
Epoch 3/20
Epoch 3/20
164/164 - 7s - loss: 0.0012 - val_loss: 0.0010 - 7s/epoch - 40ms/step
Epoch 4/20
164/164 - 7s - loss: 0.0012 - val_loss: 9.6237e-04 - 7s/epoch - 41ms/step
Epoch 5/20
164/164 - 6s - loss: 8.9916e-04 - val loss: 0.0011 - 6s/epoch - 39ms/step
Epoch 6/20
164/164 - 6s - loss: 0.0017 - val_loss: 1.3481e-04 - 6s/epoch - 38ms/step
Epoch 7/20
164/164 - 6s - loss: 0.0019 - val_loss: 5.1447e-04 - 6s/epoch - 38ms/step
Epoch 8/20
164/164 - 15s - loss: 0.0020 - val_loss: 2.4903e-05 - 15s/epoch - 91ms/step
Epoch 9/20
164/164 - 6s - loss: 0.0013 - val_loss: 2.5799e-04 - 6s/epoch - 38ms/step
Epoch 10/20
164/164 - 7s - loss: 0.0012 - val_loss: 5.0018e-04 - 7s/epoch - 40ms/step
Epoch 11/20
164/164 - 6s - loss: 9.8770e-04 - val_loss: 1.3661e-04 - 6s/epoch - 39ms/step
Epoch 12/20
164/164 - 6s - loss: 8.2273e-04 - val_loss: 5.9222e-04 - 6s/epoch - 38ms/step
Epoch 13/20
164/164 - 7s - loss: 9.6942e-04 - val_loss: 1.1432e-04 - 7s/epoch - 40ms/step
Epoch 14/20
164/164 - 6s - loss: 9.9663e-04 - val_loss: 1.8816e-05 - 6s/epoch - 38ms/step
Epoch 15/20
164/164 - 6s - loss: 8.5629e-04 - val_loss: 3.1799e-05 - 6s/epoch - 38ms/step
Epoch 16/20
164/164 - 6s - loss: 0.0016 - val_loss: 8.2456e-05 - 6s/epoch - 38ms/step
Epoch 17/20
164/164 - 6s - loss: 0.0185 - val_loss: 0.0013 - 6s/epoch - 37ms/step
Epoch 18/20
164/164 - 6s - loss: 0.0173 - val_loss: 3.8717e-04 - 6s/epoch - 38ms/step
Epoch 19/20
164/164 - 6s - loss: 0.0020 - val_loss: 8.2168e-04 - 6s/epoch - 38ms/step
Epoch 20/20
164/164 - 6s - loss: 0.0015 - val_loss: 5.4538e-04 - 6s/epoch - 38ms/step
```

```
44/44 [========] - 4s 37ms/step
```

```
[]: def visualize_model(y_test, y_pred, num_samples=500):
    # Actual data
    last_n_actual = y_test[-num_samples:]
    plt.figure(figsize=(12, 6))
    plt.plot(last_n_actual, label='Actual')
    # Predicted data
    last_n_predicted = y_pred[-num_samples:]
    plt.plot(last_n_predicted, label='Predicted')
    plt.title('Actual vs Predicted Vehicle Count')
    plt.xlabel('Index')
    plt.ylabel('Vehicle Count')
    plt.legend()
    plt.show()
```

```
[]: def visualize_loss(loss, val_loss):
    plt.plot(loss, label='Training Loss')
    plt.plot(val_loss, label='Validation Loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()
    print()
```

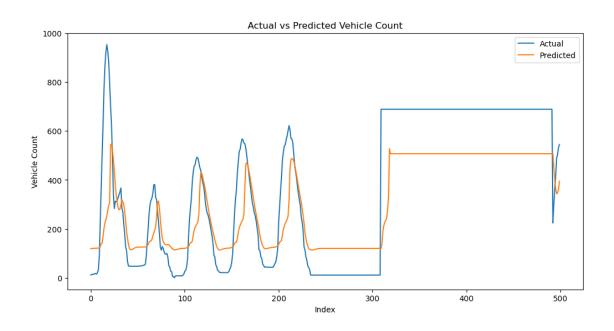
```
[]: # Print results
for area_id, result in results.items():
    print(f"Parking Area: {area_id}")
    print(f"Train Loss: {result['train_loss']}")
    print(f"Test Loss: {result['test_loss']}")
    print(f"MAE: {result['mae']}")
    print()
    # Plot training and validation loss
    visualize_loss(result['loss'], result['val_loss'])
    # Plot actual vs predicted vehicle count
    visualize_model(result['y_test'], result['y_test_pred'])
```

Parking Area: BRUUNS

Train Loss: 0.027039937674999237 Test Loss: 0.042578406631946564

MAE: 140.03030830051588

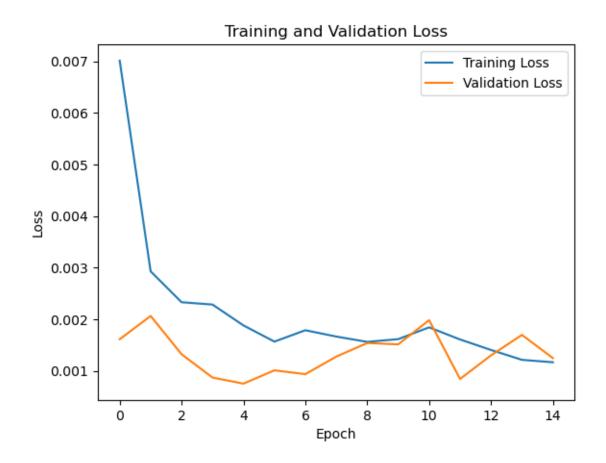


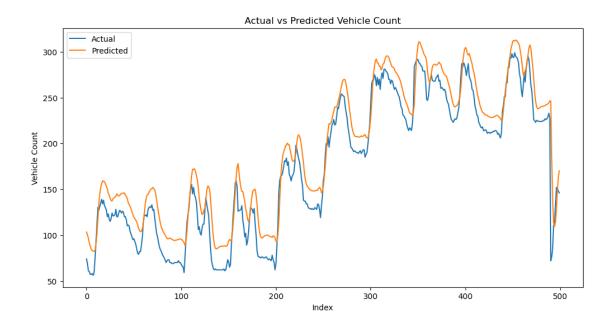


Parking Area: BUSGADEHUSET

Train Loss: 0.0016828645020723343 Test Loss: 0.0012969761155545712

MAE: 21.165626874177352

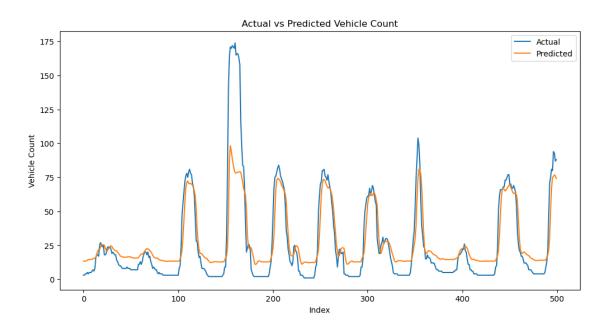




Parking Area: KALKVAERKSVEJ Train Loss: 0.004140314646065235 Test Loss: 0.005991010926663876

MAE: 9.891131630496702

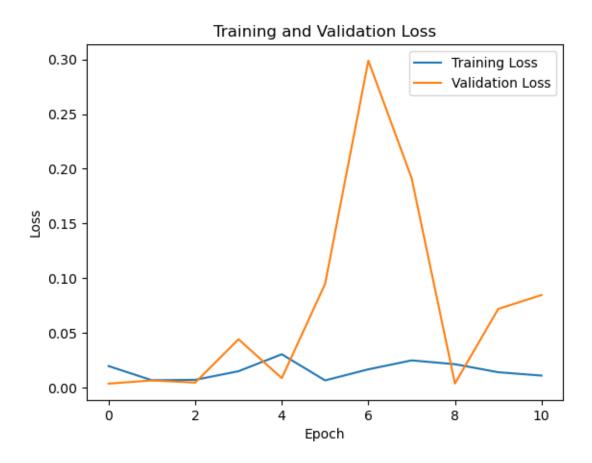


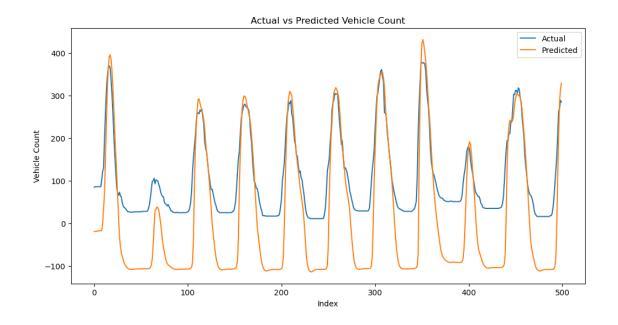


Parking Area: MAGASIN

Train Loss: 0.08427707105875015 Test Loss: 0.08309940248727798

MAE: 93.17207041204624

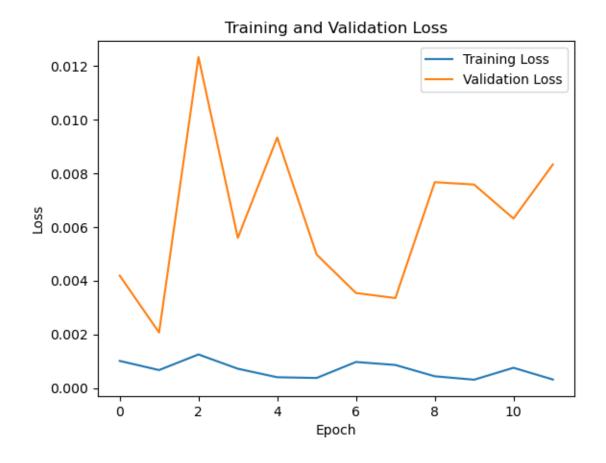


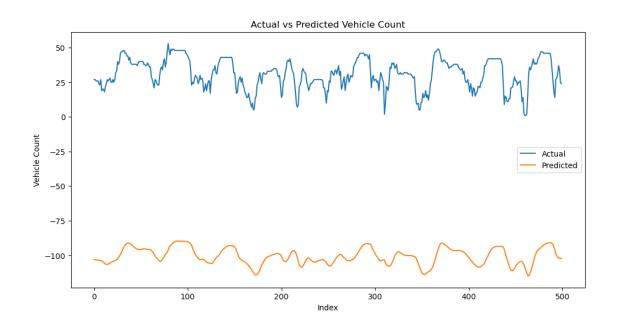


Parking Area: NORREPORT

Train Loss: 0.008291160687804222 Test Loss: 0.008081809617578983

MAE: 131.3723039654718

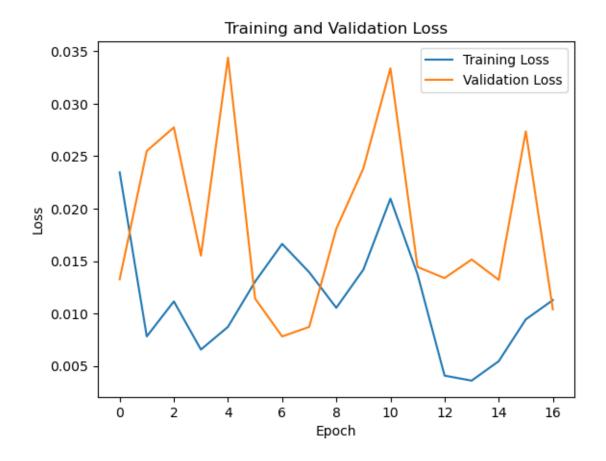


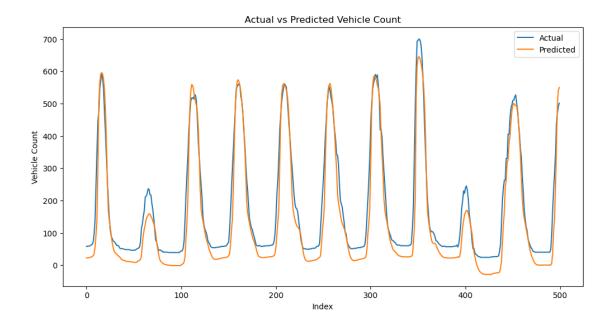


Parking Area: SALLING

Train Loss: 0.006595633924007416 Test Loss: 0.0059807924553751945

MAE: 42.602102019778194



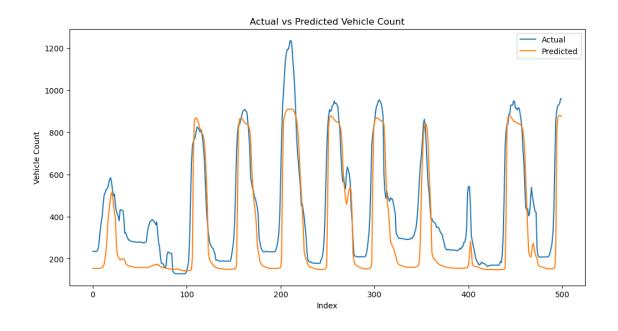


Parking Area: SCANDCENTER

Train Loss: 0.014675114303827286 Test Loss: 0.014928326942026615

MAE: 97.48193927709607

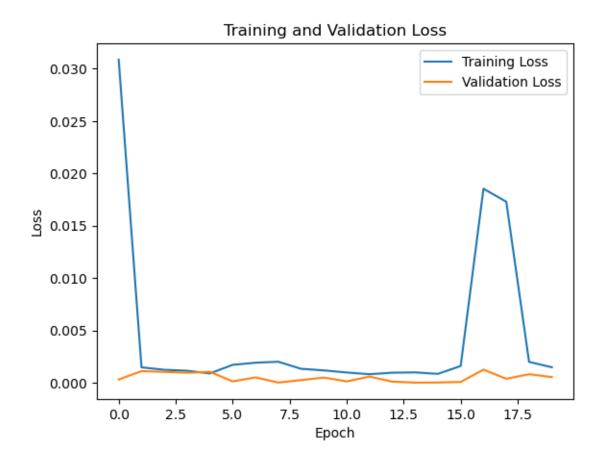


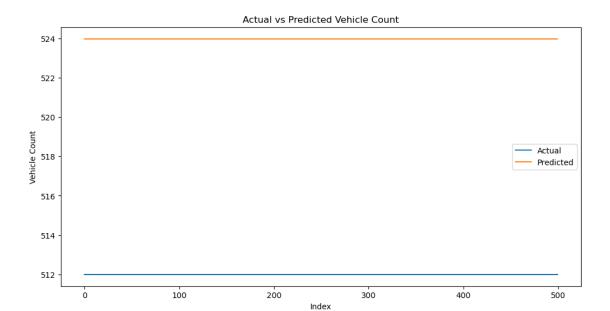


Parking Area: SKOLEBAKKEN

Train Loss: 0.024254340678453445 Test Loss: 0.000545378599781543

MAE: 11.980285821444747





1.0.6 Creating the RNN Model

```
[]: # Basing off the LSTM Model

# Create the results dictionary to store the RNN results

rnn_results = {}
```

```
[]: for area_id, area_data in df.groupby('garagecode'):
         # Extracting only the occupancy values
         occupancy = area_data[['vehiclecount']]
         # Normalize the occupancy dataset
         occupancy_scaled = scaler.fit_transform(occupancy)
         # Create sequences and labels
         X, y = create_sequences(occupancy_scaled, sequence_length)
         # Split data into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,__
      →random_state=42, shuffle=False)
         print("Number of samples in X_train:", len(X_train))
         print("Number of samples in y_train:", len(y_train))
         print("Number of samples in X_train:", X_test.shape)
         print("Number of samples in y_train:", y_test.shape)
         # # Define the RNN model
         model = Sequential()
```

```
model.
add(SimpleRNN(2,input_shape=(sequence length,1),return_sequences=True))
  model.add(TimeDistributed(Dense(units=1, activation='linear')))
  model.add(GlobalAveragePooling1D())
  model.compile(optimizer='adam', loss='mean_squared_error')
  # Model Path
  model_path = "model_rnn.h5"
  # Train the model
  history = model.fit(X_train, y_train, epochs=20, batch_size=32,__
⇒validation_split=0.05, verbose=2,
                  callbacks = [keras.callbacks.
⊸EarlyStopping(monitor='val_loss', min_delta=0, patience=10, verbose=0, __

mode='min'),
                  keras.callbacks.
-ModelCheckpoint(model_path,monitor='val_loss', save_best_only=True,_
→mode='min', verbose=0)])
  # Evaluate the model
  train_loss = model.evaluate(X_train, y_train, verbose=0)
  test_loss = model.evaluate(X_test, y_test, verbose=0)
  print("Number of samples in train_loss:", train_loss)
  print("Number of samples in test_loss:", test_loss)
  # Predict occupancy values on testing set
  y_test_pred = model.predict(X_test)
  print("Number of samples in y_test_pred:", len(y_test_pred))
  # Inverse transform the predicted and actual values to their original scale
  y_test = scaler.inverse_transform(y_test.reshape(-1, 1)).flatten()
  y_test_pred = scaler.inverse_transform(y_test_pred.reshape(-1, 1)).flatten()
  print("Number of samples in y_test:", len(y_test))
  print("Number of samples in y_test_pred:", len(y_test_pred))
  # Calculate Mean Absolute Error (MAE)
  mae = mean_absolute_error(y_test, y_test_pred)
  # Store results in the dictionary
  rnn_results[area_id] = {
       'train_loss': train_loss,
```

```
'test_loss': test_loss,
         'mae': mae,
         'loss':history.history['loss'],
         'val_loss':history.history['val_loss'],
         'y_test_pred': y_test_pred,
        'y_test': y_test
    }
Number of samples in X_train: 5518
Number of samples in y_train: 5518
Number of samples in X_train: (1380, 10, 1)
Number of samples in y_train: (1380, 1)
Epoch 1/20
164/164 - 10s - loss: 0.3949 - val loss: 0.3318 - 10s/epoch - 59ms/step
Epoch 2/20
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/keras/src/engine/training.py:3103: UserWarning:
You are saving your model as an HDF5 file via `model.save()`. This file format
is considered legacy. We recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
164/164 - 7s - loss: 0.1752 - val_loss: 0.1830 - 7s/epoch - 43ms/step
Epoch 3/20
164/164 - 7s - loss: 0.1076 - val_loss: 0.1181 - 7s/epoch - 42ms/step
Epoch 4/20
164/164 - 7s - loss: 0.0713 - val_loss: 0.0778 - 7s/epoch - 42ms/step
Epoch 5/20
164/164 - 7s - loss: 0.0474 - val loss: 0.0521 - 7s/epoch - 41ms/step
Epoch 6/20
164/164 - 7s - loss: 0.0338 - val_loss: 0.0410 - 7s/epoch - 44ms/step
Epoch 7/20
164/164 - 7s - loss: 0.0290 - val_loss: 0.0384 - 7s/epoch - 45ms/step
Epoch 8/20
164/164 - 7s - loss: 0.0279 - val_loss: 0.0371 - 7s/epoch - 42ms/step
Epoch 9/20
164/164 - 7s - loss: 0.0272 - val_loss: 0.0359 - 7s/epoch - 40ms/step
Epoch 10/20
164/164 - 6s - loss: 0.0267 - val_loss: 0.0352 - 6s/epoch - 40ms/step
Epoch 11/20
164/164 - 6s - loss: 0.0260 - val loss: 0.0343 - 6s/epoch - 39ms/step
Epoch 12/20
164/164 - 6s - loss: 0.0252 - val loss: 0.0333 - 6s/epoch - 38ms/step
Epoch 13/20
```

164/164 - 7s - loss: 0.0239 - val_loss: 0.0305 - 7s/epoch - 41ms/step

164/164 - 6s - loss: 0.0216 - val_loss: 0.0280 - 6s/epoch - 39ms/step

Epoch 14/20

```
Epoch 15/20
164/164 - 7s - loss: 0.0191 - val_loss: 0.0248 - 7s/epoch - 41ms/step
Epoch 16/20
164/164 - 7s - loss: 0.0169 - val_loss: 0.0224 - 7s/epoch - 41ms/step
Epoch 17/20
164/164 - 7s - loss: 0.0153 - val_loss: 0.0208 - 7s/epoch - 41ms/step
Epoch 18/20
164/164 - 7s - loss: 0.0141 - val_loss: 0.0201 - 7s/epoch - 40ms/step
Epoch 19/20
164/164 - 7s - loss: 0.0134 - val_loss: 0.0194 - 7s/epoch - 42ms/step
Epoch 20/20
164/164 - 6s - loss: 0.0130 - val loss: 0.0191 - 6s/epoch - 39ms/step
Number of samples in train_loss: 0.013072654604911804
Number of samples in test_loss: 0.02283564582467079
44/44 [======] - 1s 13ms/step
Number of samples in y_test_pred: 1380
Number of samples in y_test: 1380
Number of samples in y_test_pred: 1380
Number of samples in X_train: 5518
Number of samples in y_train: 5518
Number of samples in X_train: (1380, 10, 1)
Number of samples in y_train: (1380, 1)
Epoch 1/20
164/164 - 10s - loss: 0.1155 - val_loss: 0.0269 - 10s/epoch - 60ms/step
Epoch 2/20
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/keras/src/engine/training.py:3103: UserWarning:
You are saving your model as an HDF5 file via `model.save()`. This file format
is considered legacy. We recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
164/164 - 7s - loss: 0.0467 - val_loss: 0.0101 - 7s/epoch - 42ms/step
Epoch 3/20
164/164 - 7s - loss: 0.0334 - val_loss: 0.0065 - 7s/epoch - 41ms/step
Epoch 4/20
164/164 - 7s - loss: 0.0232 - val_loss: 0.0043 - 7s/epoch - 42ms/step
Epoch 5/20
164/164 - 7s - loss: 0.0168 - val_loss: 0.0035 - 7s/epoch - 41ms/step
Epoch 6/20
164/164 - 7s - loss: 0.0126 - val loss: 0.0034 - 7s/epoch - 40ms/step
Epoch 7/20
164/164 - 7s - loss: 0.0094 - val loss: 0.0032 - 7s/epoch - 41ms/step
Epoch 8/20
164/164 - 7s - loss: 0.0069 - val loss: 0.0029 - 7s/epoch - 43ms/step
```

164/164 - 10s - loss: 0.0050 - val loss: 0.0023 - 10s/epoch - 58ms/step

Epoch 9/20

```
Epoch 10/20
164/164 - 8s - loss: 0.0038 - val_loss: 0.0019 - 8s/epoch - 51ms/step
Epoch 11/20
164/164 - 8s - loss: 0.0031 - val_loss: 0.0017 - 8s/epoch - 49ms/step
Epoch 12/20
164/164 - 7s - loss: 0.0028 - val_loss: 0.0017 - 7s/epoch - 42ms/step
Epoch 13/20
164/164 - 7s - loss: 0.0026 - val_loss: 0.0017 - 7s/epoch - 42ms/step
Epoch 14/20
164/164 - 7s - loss: 0.0025 - val_loss: 0.0017 - 7s/epoch - 43ms/step
Epoch 15/20
164/164 - 9s - loss: 0.0025 - val loss: 0.0016 - 9s/epoch - 56ms/step
Epoch 16/20
164/164 - 9s - loss: 0.0024 - val loss: 0.0016 - 9s/epoch - 55ms/step
Epoch 17/20
164/164 - 7s - loss: 0.0024 - val loss: 0.0016 - 7s/epoch - 43ms/step
Epoch 18/20
164/164 - 7s - loss: 0.0023 - val loss: 0.0016 - 7s/epoch - 42ms/step
Epoch 19/20
164/164 - 7s - loss: 0.0023 - val_loss: 0.0016 - 7s/epoch - 42ms/step
Epoch 20/20
164/164 - 7s - loss: 0.0023 - val_loss: 0.0016 - 7s/epoch - 41ms/step
Number of samples in train_loss: 0.0022882225457578897
Number of samples in test_loss: 0.001360987196676433
44/44 [========] - 1s 25ms/step
Number of samples in y_test_pred: 1380
Number of samples in y_test: 1380
Number of samples in y_test_pred: 1380
Number of samples in X_train: 5518
Number of samples in y_train: 5518
Number of samples in X_train: (1380, 10, 1)
Number of samples in y_train: (1380, 1)
Epoch 1/20
164/164 - 10s - loss: 0.0252 - val_loss: 0.0165 - 10s/epoch - 63ms/step
Epoch 2/20
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/keras/src/engine/training.py:3103: UserWarning:
You are saving your model as an HDF5 file via `model.save()`. This file format
is considered legacy. We recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')`.
164/164 - 7s - loss: 0.0106 - val loss: 0.0142 - 7s/epoch - 42ms/step
Epoch 3/20
164/164 - 7s - loss: 0.0093 - val loss: 0.0138 - 7s/epoch - 43ms/step
Epoch 4/20
164/164 - 8s - loss: 0.0090 - val loss: 0.0137 - 8s/epoch - 50ms/step
```

```
Epoch 5/20
164/164 - 7s - loss: 0.0088 - val_loss: 0.0135 - 7s/epoch - 43ms/step
Epoch 6/20
164/164 - 7s - loss: 0.0086 - val_loss: 0.0132 - 7s/epoch - 45ms/step
Epoch 7/20
164/164 - 7s - loss: 0.0085 - val_loss: 0.0131 - 7s/epoch - 42ms/step
Epoch 8/20
164/164 - 7s - loss: 0.0083 - val_loss: 0.0128 - 7s/epoch - 40ms/step
Epoch 9/20
164/164 - 8s - loss: 0.0081 - val_loss: 0.0125 - 8s/epoch - 46ms/step
Epoch 10/20
164/164 - 8s - loss: 0.0079 - val_loss: 0.0124 - 8s/epoch - 48ms/step
Epoch 11/20
164/164 - 7s - loss: 0.0077 - val_loss: 0.0121 - 7s/epoch - 41ms/step
Epoch 12/20
164/164 - 7s - loss: 0.0074 - val loss: 0.0116 - 7s/epoch - 41ms/step
Epoch 13/20
164/164 - 7s - loss: 0.0072 - val loss: 0.0115 - 7s/epoch - 41ms/step
Epoch 14/20
164/164 - 7s - loss: 0.0070 - val_loss: 0.0112 - 7s/epoch - 41ms/step
Epoch 15/20
164/164 - 6s - loss: 0.0068 - val_loss: 0.0109 - 6s/epoch - 39ms/step
Epoch 16/20
164/164 - 7s - loss: 0.0065 - val_loss: 0.0106 - 7s/epoch - 44ms/step
Epoch 17/20
164/164 - 7s - loss: 0.0063 - val loss: 0.0104 - 7s/epoch - 43ms/step
Epoch 18/20
164/164 - 7s - loss: 0.0061 - val_loss: 0.0100 - 7s/epoch - 42ms/step
Epoch 19/20
164/164 - 7s - loss: 0.0059 - val_loss: 0.0097 - 7s/epoch - 40ms/step
Epoch 20/20
164/164 - 7s - loss: 0.0057 - val_loss: 0.0094 - 7s/epoch - 44ms/step
Number of samples in train_loss: 0.005770742893218994
Number of samples in test_loss: 0.008282957598567009
44/44 [======== ] - 1s 14ms/step
Number of samples in y_test_pred: 1380
Number of samples in y test: 1380
Number of samples in y_test_pred: 1380
Number of samples in X_train: 5518
Number of samples in y_train: 5518
Number of samples in X_train: (1380, 10, 1)
Number of samples in y_train: (1380, 1)
Epoch 1/20
164/164 - 10s - loss: 0.0665 - val loss: 0.0557 - 10s/epoch - 62ms/step
Epoch 2/20
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/keras/src/engine/training.py:3103: UserWarning:
```

```
164/164 - 8s - loss: 0.0513 - val_loss: 0.0483 - 8s/epoch - 51ms/step
Epoch 3/20
164/164 - 8s - loss: 0.0455 - val_loss: 0.0444 - 8s/epoch - 46ms/step
Epoch 4/20
164/164 - 7s - loss: 0.0424 - val_loss: 0.0422 - 7s/epoch - 44ms/step
Epoch 5/20
164/164 - 7s - loss: 0.0405 - val_loss: 0.0407 - 7s/epoch - 41ms/step
Epoch 6/20
164/164 - 7s - loss: 0.0393 - val_loss: 0.0397 - 7s/epoch - 40ms/step
Epoch 7/20
164/164 - 7s - loss: 0.0384 - val_loss: 0.0389 - 7s/epoch - 42ms/step
Epoch 8/20
164/164 - 7s - loss: 0.0376 - val_loss: 0.0382 - 7s/epoch - 41ms/step
Epoch 9/20
164/164 - 7s - loss: 0.0370 - val_loss: 0.0378 - 7s/epoch - 40ms/step
Epoch 10/20
164/164 - 7s - loss: 0.0366 - val_loss: 0.0373 - 7s/epoch - 40ms/step
Epoch 11/20
164/164 - 7s - loss: 0.0362 - val_loss: 0.0370 - 7s/epoch - 41ms/step
Epoch 12/20
164/164 - 7s - loss: 0.0359 - val_loss: 0.0367 - 7s/epoch - 41ms/step
Epoch 13/20
164/164 - 6s - loss: 0.0356 - val loss: 0.0364 - 6s/epoch - 39ms/step
Epoch 14/20
164/164 - 6s - loss: 0.0354 - val loss: 0.0362 - 6s/epoch - 38ms/step
Epoch 15/20
164/164 - 6s - loss: 0.0351 - val_loss: 0.0360 - 6s/epoch - 38ms/step
Epoch 16/20
164/164 - 7s - loss: 0.0347 - val_loss: 0.0352 - 7s/epoch - 40ms/step
Epoch 17/20
164/164 - 6s - loss: 0.0325 - val_loss: 0.0302 - 6s/epoch - 38ms/step
Epoch 18/20
164/164 - 6s - loss: 0.0270 - val_loss: 0.0253 - 6s/epoch - 39ms/step
Epoch 19/20
164/164 - 6s - loss: 0.0245 - val_loss: 0.0234 - 6s/epoch - 39ms/step
Epoch 20/20
164/164 - 7s - loss: 0.0234 - val_loss: 0.0225 - 7s/epoch - 41ms/step
Number of samples in train_loss: 0.02296583727002144
Number of samples in test_loss: 0.025660675019025803
44/44 [======== ] - 1s 15ms/step
Number of samples in y_test_pred: 1380
Number of samples in y_test: 1380
```

```
Number of samples in y_test_pred: 1380

Number of samples in X_train: 5518

Number of samples in y_train: 5518

Number of samples in X_train: (1380, 10, 1)

Number of samples in y_train: (1380, 1)

Epoch 1/20

164/164 - 10s - loss: 2.3303e-04 - val_loss: 5.9379e-05 - 10s/epoch - 60ms/step

Epoch 2/20
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 2.2675e-04 - val_loss: 8.8931e-05 - 7s/epoch - 43ms/step
Epoch 3/20
164/164 - 7s - loss: 2.2695e-04 - val_loss: 6.0403e-05 - 7s/epoch - 43ms/step
Epoch 4/20
164/164 - 7s - loss: 2.2546e-04 - val_loss: 5.9045e-05 - 7s/epoch - 43ms/step
Epoch 5/20
164/164 - 7s - loss: 2.2458e-04 - val_loss: 5.8255e-05 - 7s/epoch - 41ms/step
Epoch 6/20
164/164 - 7s - loss: 2.2475e-04 - val_loss: 5.8282e-05 - 7s/epoch - 40ms/step
Epoch 7/20
164/164 - 6s - loss: 2.2488e-04 - val loss: 5.8968e-05 - 6s/epoch - 39ms/step
Epoch 8/20
164/164 - 7s - loss: 2.2350e-04 - val_loss: 8.0224e-05 - 7s/epoch - 41ms/step
Epoch 9/20
164/164 - 6s - loss: 2.2457e-04 - val_loss: 6.5675e-05 - 6s/epoch - 39ms/step
Epoch 10/20
164/164 - 7s - loss: 2.2371e-04 - val loss: 5.4959e-05 - 7s/epoch - 40ms/step
Epoch 11/20
164/164 - 8s - loss: 2.2208e-04 - val loss: 5.5571e-05 - 8s/epoch - 46ms/step
Epoch 12/20
164/164 - 7s - loss: 2.2230e-04 - val loss: 5.6708e-05 - 7s/epoch - 41ms/step
Epoch 13/20
164/164 - 7s - loss: 2.2225e-04 - val_loss: 5.8330e-05 - 7s/epoch - 45ms/step
Epoch 14/20
164/164 - 8s - loss: 2.2127e-04 - val_loss: 5.7320e-05 - 8s/epoch - 46ms/step
Epoch 15/20
164/164 - 7s - loss: 2.2165e-04 - val_loss: 5.2290e-05 - 7s/epoch - 41ms/step
Epoch 16/20
164/164 - 7s - loss: 2.1951e-04 - val_loss: 5.2689e-05 - 7s/epoch - 43ms/step
Epoch 17/20
164/164 - 6s - loss: 2.1911e-04 - val_loss: 5.1506e-05 - 6s/epoch - 39ms/step
Epoch 18/20
```

```
164/164 - 6s - loss: 2.1917e-04 - val loss: 5.3534e-05 - 6s/epoch - 39ms/step
Epoch 19/20
164/164 - 7s - loss: 2.1971e-04 - val_loss: 4.9857e-05 - 7s/epoch - 40ms/step
Epoch 20/20
164/164 - 7s - loss: 2.1833e-04 - val loss: 5.0121e-05 - 7s/epoch - 40ms/step
Number of samples in train_loss: 0.00020719203166663647
Number of samples in test loss: 3.259140066802502e-05
44/44 [======== ] - 1s 19ms/step
Number of samples in y_test_pred: 1380
Number of samples in y_test: 1380
Number of samples in y_test_pred: 1380
Number of samples in X_train: 5518
Number of samples in y_train: 5518
Number of samples in X_train: (1380, 10, 1)
Number of samples in y_train: (1380, 1)
Epoch 1/20
164/164 - 10s - loss: 0.2097 - val_loss: 0.2677 - 10s/epoch - 62ms/step
Epoch 2/20
```

/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 0.1082 - val loss: 0.1704 - 7s/epoch - 41ms/step
Epoch 3/20
164/164 - 7s - loss: 0.0845 - val_loss: 0.1373 - 7s/epoch - 40ms/step
Epoch 4/20
164/164 - 7s - loss: 0.0760 - val loss: 0.1231 - 7s/epoch - 43ms/step
Epoch 5/20
164/164 - 7s - loss: 0.0712 - val loss: 0.1151 - 7s/epoch - 40ms/step
Epoch 6/20
164/164 - 7s - loss: 0.0679 - val loss: 0.1095 - 7s/epoch - 40ms/step
Epoch 7/20
164/164 - 7s - loss: 0.0656 - val_loss: 0.1057 - 7s/epoch - 40ms/step
Epoch 8/20
164/164 - 7s - loss: 0.0639 - val_loss: 0.1034 - 7s/epoch - 40ms/step
Epoch 9/20
164/164 - 7s - loss: 0.0625 - val_loss: 0.1016 - 7s/epoch - 40ms/step
Epoch 10/20
164/164 - 7s - loss: 0.0614 - val_loss: 0.1003 - 7s/epoch - 41ms/step
Epoch 11/20
164/164 - 6s - loss: 0.0605 - val_loss: 0.0982 - 6s/epoch - 39ms/step
Epoch 12/20
164/164 - 7s - loss: 0.0597 - val_loss: 0.0966 - 7s/epoch - 41ms/step
Epoch 13/20
```

```
164/164 - 7s - loss: 0.0589 - val loss: 0.0952 - 7s/epoch - 40ms/step
Epoch 14/20
164/164 - 7s - loss: 0.0581 - val loss: 0.0945 - 7s/epoch - 41ms/step
Epoch 15/20
164/164 - 7s - loss: 0.0568 - val loss: 0.0921 - 7s/epoch - 40ms/step
Epoch 16/20
164/164 - 6s - loss: 0.0541 - val loss: 0.0844 - 6s/epoch - 39ms/step
Epoch 17/20
164/164 - 6s - loss: 0.0499 - val_loss: 0.0728 - 6s/epoch - 39ms/step
Epoch 18/20
164/164 - 6s - loss: 0.0437 - val loss: 0.0594 - 6s/epoch - 39ms/step
Epoch 19/20
164/164 - 7s - loss: 0.0352 - val loss: 0.0445 - 7s/epoch - 40ms/step
Epoch 20/20
164/164 - 6s - loss: 0.0271 - val_loss: 0.0341 - 6s/epoch - 40ms/step
Number of samples in train_loss: 0.02472447231411934
Number of samples in test_loss: 0.032257311046123505
44/44 [======] - 1s 18ms/step
Number of samples in y_test_pred: 1380
Number of samples in y_test: 1380
Number of samples in y_test_pred: 1380
Number of samples in X_train: 5518
Number of samples in y_train: 5518
Number of samples in X_train: (1380, 10, 1)
Number of samples in y_train: (1380, 1)
Epoch 1/20
164/164 - 10s - loss: 0.0451 - val_loss: 0.0332 - 10s/epoch - 63ms/step
Epoch 2/20
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
```

packages/keras/src/engine/training.py:3103: UserWarning:

```
164/164 - 7s - loss: 0.0267 - val loss: 0.0276 - 7s/epoch - 42ms/step
Epoch 3/20
164/164 - 7s - loss: 0.0223 - val_loss: 0.0235 - 7s/epoch - 41ms/step
Epoch 4/20
164/164 - 7s - loss: 0.0190 - val_loss: 0.0203 - 7s/epoch - 42ms/step
Epoch 5/20
164/164 - 7s - loss: 0.0165 - val_loss: 0.0179 - 7s/epoch - 41ms/step
Epoch 6/20
164/164 - 7s - loss: 0.0148 - val_loss: 0.0164 - 7s/epoch - 40ms/step
Epoch 7/20
164/164 - 6s - loss: 0.0140 - val_loss: 0.0156 - 6s/epoch - 40ms/step
Epoch 8/20
```

```
164/164 - 7s - loss: 0.0135 - val_loss: 0.0150 - 7s/epoch - 41ms/step
Epoch 9/20
164/164 - 7s - loss: 0.0132 - val loss: 0.0146 - 7s/epoch - 41ms/step
Epoch 10/20
164/164 - 7s - loss: 0.0128 - val loss: 0.0141 - 7s/epoch - 41ms/step
Epoch 11/20
164/164 - 7s - loss: 0.0125 - val loss: 0.0135 - 7s/epoch - 41ms/step
Epoch 12/20
164/164 - 7s - loss: 0.0121 - val_loss: 0.0128 - 7s/epoch - 41ms/step
Epoch 13/20
164/164 - 7s - loss: 0.0117 - val loss: 0.0122 - 7s/epoch - 43ms/step
Epoch 14/20
164/164 - 7s - loss: 0.0114 - val_loss: 0.0118 - 7s/epoch - 43ms/step
Epoch 15/20
164/164 - 7s - loss: 0.0111 - val_loss: 0.0114 - 7s/epoch - 44ms/step
Epoch 16/20
164/164 - 8s - loss: 0.0109 - val_loss: 0.0112 - 8s/epoch - 47ms/step
Epoch 17/20
164/164 - 7s - loss: 0.0107 - val_loss: 0.0112 - 7s/epoch - 40ms/step
Epoch 18/20
164/164 - 6s - loss: 0.0106 - val_loss: 0.0110 - 6s/epoch - 39ms/step
Epoch 19/20
164/164 - 6s - loss: 0.0105 - val_loss: 0.0111 - 6s/epoch - 39ms/step
Epoch 20/20
164/164 - 6s - loss: 0.0105 - val_loss: 0.0109 - 6s/epoch - 39ms/step
Number of samples in train_loss: 0.010432455688714981
Number of samples in test_loss: 0.01267289835959673
44/44 [======] - 1s 21ms/step
Number of samples in y_test_pred: 1380
Number of samples in y_test: 1380
Number of samples in y_test_pred: 1380
Number of samples in X_train: 5518
Number of samples in y_train: 5518
Number of samples in X_train: (1380, 10, 1)
Number of samples in y_train: (1380, 1)
Epoch 1/20
164/164 - 10s - loss: 0.9984 - val_loss: 0.8115 - 10s/epoch - 62ms/step
Epoch 2/20
/Users/kseniakoldaeva/anaconda3/lib/python3.11/site-
packages/keras/src/engine/training.py:3103: UserWarning:
```

```
164/164 - 7s - loss: 0.3591 - val_loss: 0.2274 - 7s/epoch - 42ms/step Epoch 3/20
```

```
164/164 - 7s - loss: 0.1141 - val_loss: 0.0482 - 7s/epoch - 44ms/step
    Epoch 4/20
    164/164 - 7s - loss: 0.0285 - val_loss: 0.0080 - 7s/epoch - 42ms/step
    Epoch 5/20
    164/164 - 7s - loss: 0.0085 - val_loss: 0.0012 - 7s/epoch - 40ms/step
    Epoch 6/20
    164/164 - 7s - loss: 0.0032 - val_loss: 2.0310e-04 - 7s/epoch - 41ms/step
    Epoch 7/20
    164/164 - 7s - loss: 0.0018 - val_loss: 2.9406e-05 - 7s/epoch - 41ms/step
    Epoch 8/20
    164/164 - 7s - loss: 0.0015 - val_loss: 2.8431e-06 - 7s/epoch - 40ms/step
    Epoch 9/20
    164/164 - 7s - loss: 0.0014 - val_loss: 1.5858e-07 - 7s/epoch - 40ms/step
    Epoch 10/20
    164/164 - 7s - loss: 0.0014 - val_loss: 1.5806e-07 - 7s/epoch - 41ms/step
    Epoch 11/20
    164/164 - 7s - loss: 0.0014 - val_loss: 2.2597e-08 - 7s/epoch - 40ms/step
    Epoch 12/20
    164/164 - 6s - loss: 0.0014 - val loss: 1.9973e-07 - 6s/epoch - 39ms/step
    Epoch 13/20
    164/164 - 6s - loss: 0.0014 - val_loss: 1.4482e-08 - 6s/epoch - 39ms/step
    Epoch 14/20
    164/164 - 7s - loss: 0.0013 - val_loss: 3.0168e-07 - 7s/epoch - 40ms/step
    Epoch 15/20
    164/164 - 6s - loss: 0.0013 - val_loss: 2.5346e-08 - 6s/epoch - 39ms/step
    Epoch 16/20
    164/164 - 7s - loss: 0.0013 - val_loss: 8.2894e-07 - 7s/epoch - 41ms/step
    Epoch 17/20
    164/164 - 6s - loss: 0.0013 - val_loss: 2.9468e-08 - 6s/epoch - 39ms/step
    Epoch 18/20
    164/164 - 6s - loss: 0.0013 - val_loss: 1.2426e-07 - 6s/epoch - 39ms/step
    Epoch 19/20
    164/164 - 6s - loss: 0.0013 - val_loss: 3.3228e-07 - 6s/epoch - 39ms/step
    Epoch 20/20
    164/164 - 6s - loss: 0.0013 - val_loss: 2.0989e-06 - 6s/epoch - 38ms/step
    Number of samples in train loss: 0.0012448214692994952
    Number of samples in test_loss: 2.0988784399378346e-06
    44/44 [=======] - 1s 16ms/step
    Number of samples in y_test_pred: 1380
    Number of samples in y_test: 1380
    Number of samples in y_test_pred: 1380
[]: # Print results
    for area_id, rnn_result in rnn_results.items():
        print(f"Parking Area: {area_id}")
        print(f"Train Loss: {rnn_result['train_loss']}")
```

Epoch 3/20

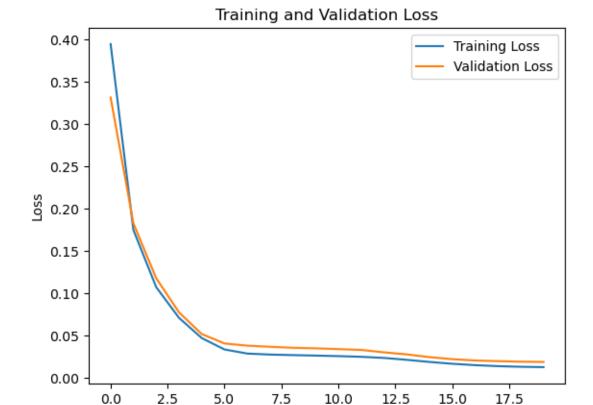
```
print(f"Test Loss: {rnn_result['test_loss']}")
print(f"MAE: {rnn_result['mae']}")
print()
# Plot training and validation loss
visualize_loss(rnn_result['loss'], rnn_result['val_loss'])

# Plot actual vs predicted vehicle count
visualize_model(rnn_result['y_test'], rnn_result['y_test_pred'])
```

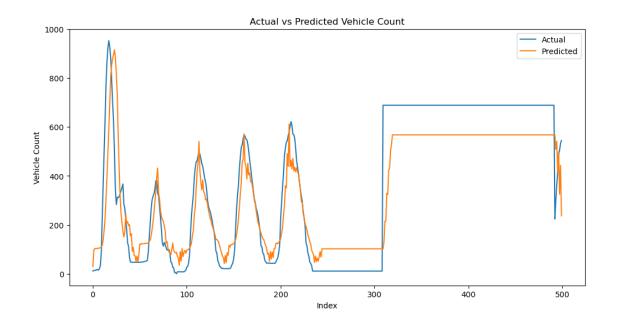
Parking Area: BRUUNS

Train Loss: 0.013072654604911804 Test Loss: 0.02283564582467079

MAE: 105.48849960202756



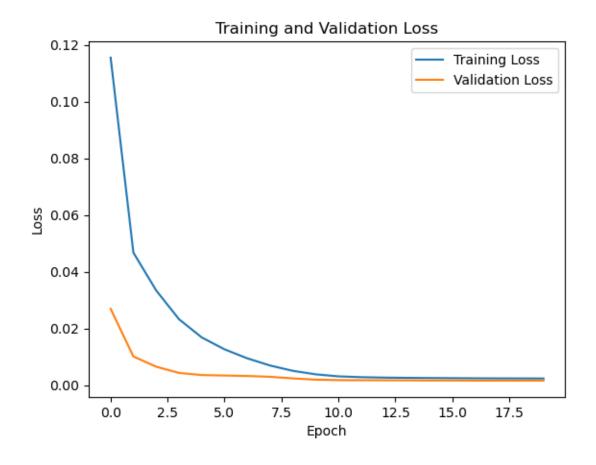
Epoch

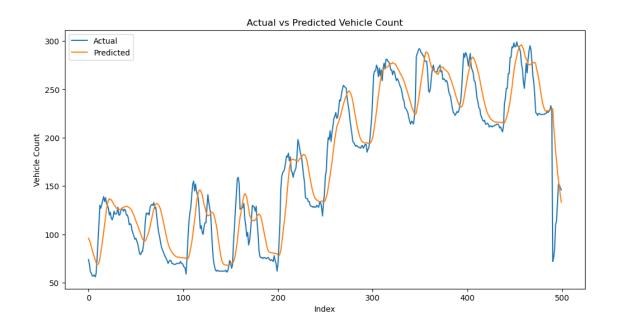


Parking Area: BUSGADEHUSET

Train Loss: 0.0022882225457578897 Test Loss: 0.001360987196676433

MAE: 18.949664256883704

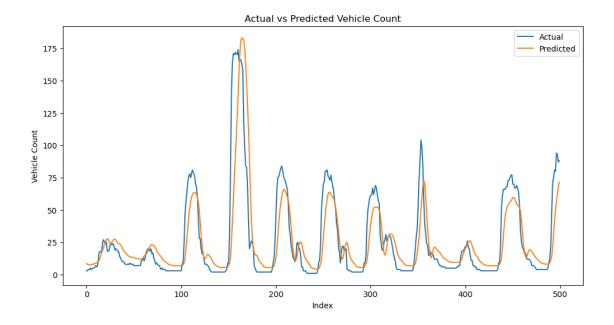




Parking Area: KALKVAERKSVEJ Train Loss: 0.005770742893218994 Test Loss: 0.008282957598567009

MAE: 10.47484705430874

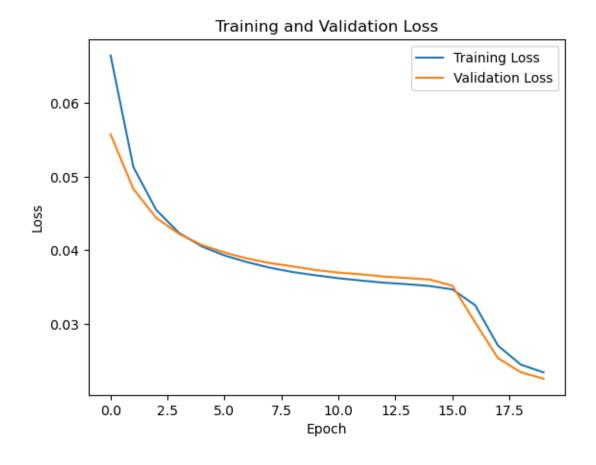


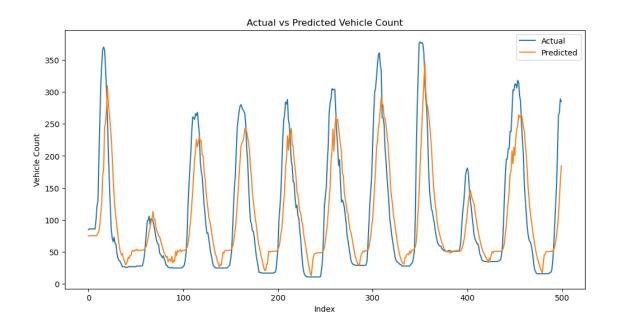


Parking Area: MAGASIN

Train Loss: 0.02296583727002144 Test Loss: 0.025660675019025803

MAE: 44.21515581711479



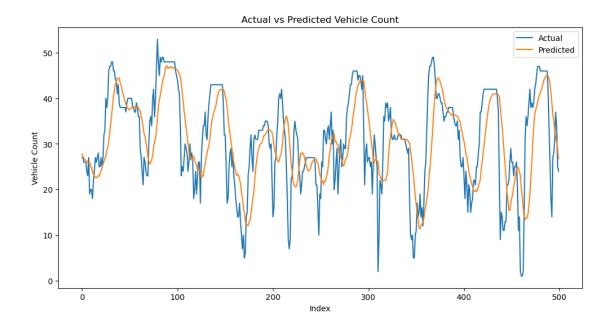


Parking Area: NORREPORT

Train Loss: 0.00020719203166663647 Test Loss: 3.259140066802502e-05

MAE: 6.345366072654724

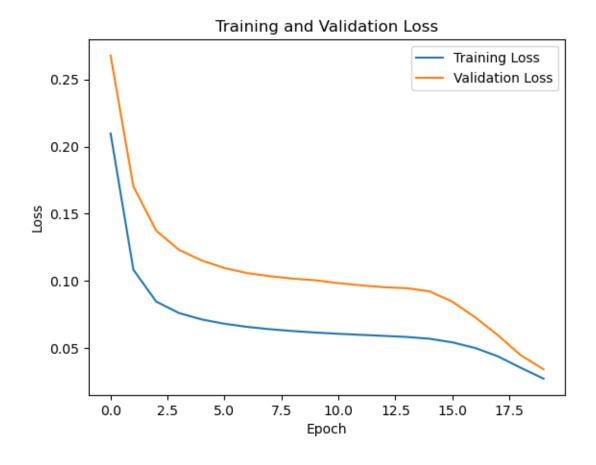


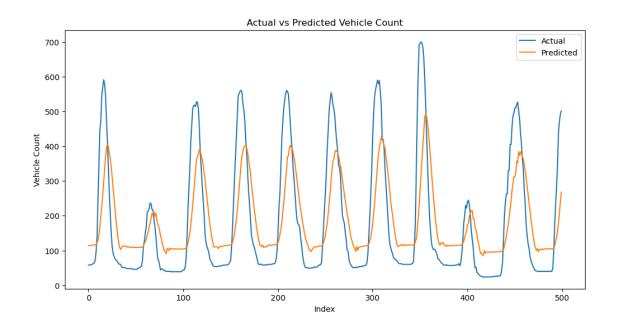


Parking Area: SALLING

Train Loss: 0.02472447231411934 Test Loss: 0.032257311046123505

MAE: 99.33057679438936

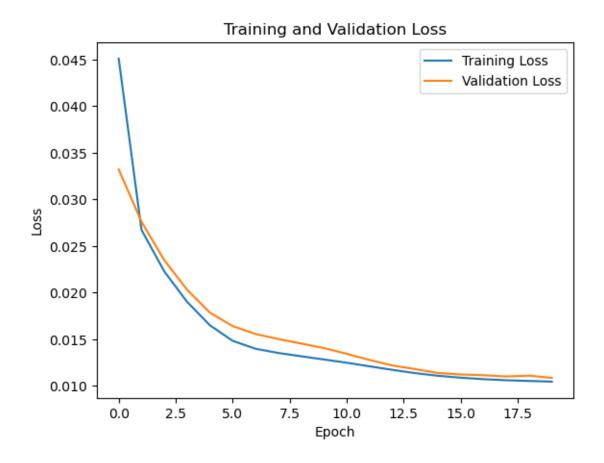


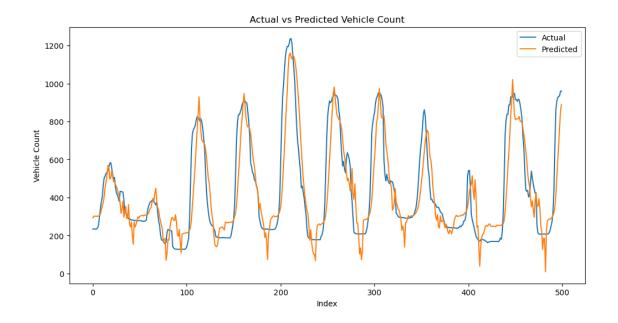


Parking Area: SCANDCENTER

Train Loss: 0.010432455688714981 Test Loss: 0.01267289835959673

MAE: 95.40104024444801





Parking Area: SKOLEBAKKEN

Train Loss: 0.0012448214692994952 Test Loss: 2.0988784399378346e-06

MAE: 0.74322509765625

