

```
In [18]: # Bike Demand Prediction + Feature Engineering + KerasTuner
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.metrics import r2_score, mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
from keras import models, layers, Input, callbacks, regularizers
from keras.losses import Huber
from keras.models import load_model
import tensorflow as tf
```

```
In [20]: # Load and preprocess data
df = pd.read_csv(r"C:/Users/91888/Downloads/Daily Bike Sharing.csv")
df['dteday'] = pd.to_datetime(df['dteday'])
df['day'] = df['dteday'].dt.day
```

```
In [21]: df.head(5)
```

```
Out[21]:
```

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt	day
0	1	2011-01-01	1	0	1	0	6	0	2	0.344167	0.363625	0.805833	0.160446	331	654	985	1
1	2	2011-01-02	1	0	1	0	0	0	2	0.363478	0.353739	0.696087	0.248539	131	670	801	2
2	3	2011-01-03	1	0	1	0	1	1	1	0.196364	0.189405	0.437273	0.248309	120	1229	1349	3
3	4	2011-01-04	1	0	1	0	2	1	1	0.200000	0.212122	0.590435	0.160296	108	1454	1562	4
4	5	2011-01-05	1	0	1	0	3	1	1	0.226957	0.229270	0.436957	0.186900	82	1518	1600	5

```
In [22]: # Additional features
df['is_weekend'] = df['weekday'].apply(lambda x: 1 if x in [0, 6] else 0)
df['week_of_year'] = df['dteday'].dt.isocalendar().week.astype(int)
df['cnt_lag1'] = df['cnt'].shift(1).fillna(method='bfill')
df['cnt_rolling_3'] = df['cnt'].rolling(3).mean().fillna(method='bfill')
```

```
C:\Users\91888\AppData\Local\Temp\ipykernel_33044\1900638960.py:4: FutureWarning: Series.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.
df['cnt_lag1'] = df['cnt'].shift(1).fillna(method='bfill')
C:\Users\91888\AppData\Local\Temp\ipykernel_33044\1900638960.py:5: FutureWarning: Series.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.
df['cnt_rolling_3'] = df['cnt'].rolling(3).mean().fillna(method='bfill')
```

```
In [23]: # Drop unneeded columns
df.drop(['instant', 'dteday', 'yr', 'casual', 'registered'], axis=1, inplace=True)
```

```
In [24]: # Categorical and numerical features
categorical_features = ['season', 'mnth', 'weekday', 'weathersit']
numerical_features = [col for col in df.columns if col not in categorical_features + ['cnt']]
print("Categorical Features:", categorical_features)
print("Numerical Features:", numerical_features)
```

```
Categorical Features: ['season', 'mnth', 'weekday', 'weathersit']
Numerical Features: ['holiday', 'workingday', 'temp', 'atemp', 'hum', 'windspeed', 'day', 'is_weekend', 'week_of_year', 'cnt_lag1', 'cnt_rolling_3']
```

```
In [25]: # Preprocessor
preprocessor = ColumnTransformer([
    ('num', MinMaxScaler(), numerical_features),
    ('cat', OneHotEncoder(drop='first'), categorical_features)
])
```

```
In [26]: # Split data
X = df.drop('cnt', axis=1)
y = df['cnt']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

















































```
In [27]: # Transform inputs
X_train_processed = preprocessor.fit_transform(X_train)
X_test_processed = preprocessor.transform(X_test)
```

```
In [28]: # Build and train neural network
model = models.Sequential([
    Input(shape=(X_train_processed.shape[1],)),
    layers.Dense(128, activation='relu', kernel_regularizer=regularizers.l2(0.001)),
    layers.Dropout(0.3),
    layers.Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.001)),
    layers.Dropout(0.3),
    layers.Dense(1, activation='linear')
])














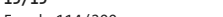



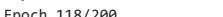


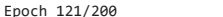
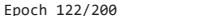
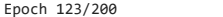
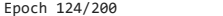
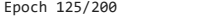
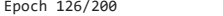
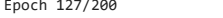
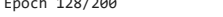
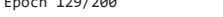
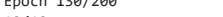
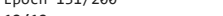
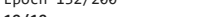
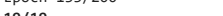
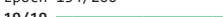















model.compile(optimizer='adam', loss=Huber(), metrics=['mae'])
early_stop = callbacks.EarlyStopping(monitor='val_loss', patience=15, restore_best_weights=True)

history = model.fit(
    X_train_processed, y_train,
    validation_data=(X_test_processed, y_test),
    epochs=200,
```

```
batch_size=32,  
callbacks=[early_stop],  
verbose=1  
)
```

Epoch 1/200
19/19  3s 32ms/step - loss: 4561.7109 - mae: 4562.0757 - val_loss: 4274.4697 - val_mae: 4274.8350
Epoch 2/200
19/19  0s 15ms/step - loss: 4615.6016 - mae: 4615.9658 - val_loss: 4264.8369 - val_mae: 4265.1973
Epoch 3/200
19/19  0s 12ms/step - loss: 4608.1450 - mae: 4608.5015 - val_loss: 4240.8989 - val_mae: 4241.2417
Epoch 4/200
19/19  0s 11ms/step - loss: 4434.6260 - mae: 4434.9634 - val_loss: 4189.9941 - val_mae: 4190.3062
Epoch 5/200
19/19  0s 11ms/step - loss: 4629.5854 - mae: 4629.8867 - val_loss: 4097.3740 - val_mae: 4097.6357
Epoch 6/200
19/19  0s 13ms/step - loss: 4240.5791 - mae: 4240.8242 - val_loss: 3947.7593 - val_mae: 3947.9482
Epoch 7/200
19/19  0s 12ms/step - loss: 4161.7275 - mae: 4161.8936 - val_loss: 3725.2551 - val_mae: 3725.3479
Epoch 8/200
19/19  0s 12ms/step - loss: 3825.3040 - mae: 3825.3687 - val_loss: 3421.4282 - val_mae: 3421.4026
Epoch 9/200
19/19  0s 11ms/step - loss: 3614.7869 - mae: 3614.7285 - val_loss: 3026.8757 - val_mae: 3026.7112
Epoch 10/200
19/19  0s 11ms/step - loss: 3147.0237 - mae: 3146.8203 - val_loss: 2550.0059 - val_mae: 2549.6807
Epoch 11/200
19/19  0s 11ms/step - loss: 2596.5520 - mae: 2596.1843 - val_loss: 2065.8347 - val_mae: 2065.3345
Epoch 12/200
19/19  0s 10ms/step - loss: 2123.4570 - mae: 2122.9141 - val_loss: 1668.1367 - val_mae: 1667.4611
Epoch 13/200
19/19  0s 12ms/step - loss: 1732.2690 - mae: 1731.5542 - val_loss: 1416.0312 - val_mae: 1415.2085
Epoch 14/200
19/19  0s 11ms/step - loss: 1389.4043 - mae: 1388.5524 - val_loss: 1324.6984 - val_mae: 1323.7694
Epoch 15/200
19/19  0s 11ms/step - loss: 1298.3461 - mae: 1297.4000 - val_loss: 1314.4110 - val_mae: 1313.4290
Epoch 16/200
19/19  0s 11ms/step - loss: 1334.0560 - mae: 1333.0680 - val_loss: 1304.9026 - val_mae: 1303.9103
Epoch 17/200
19/19  0s 11ms/step - loss: 1290.4956 - mae: 1289.5012 - val_loss: 1295.4836 - val_mae: 1294.4836
Epoch 18/200
19/19  0s 11ms/step - loss: 1279.1305 - mae: 1278.1333 - val_loss: 1278.5898 - val_mae: 1277.5950
Epoch 19/200
19/19  0s 11ms/step - loss: 1285.0354 - mae: 1284.0385 - val_loss: 1269.6560 - val_mae: 1268.6528
Epoch 20/200
19/19  0s 11ms/step - loss: 1251.5515 - mae: 1250.5498 - val_loss: 1253.8331 - val_mae: 1252.8345
Epoch 21/200
19/19  0s 11ms/step - loss: 1229.5236 - mae: 1228.5211 - val_loss: 1246.9906 - val_mae: 1245.9788
Epoch 22/200
19/19  0s 11ms/step - loss: 1218.6466 - mae: 1217.6356 - val_loss: 1228.4585 - val_mae: 1227.4536
Epoch 23/200
19/19  0s 10ms/step - loss: 1227.4746 - mae: 1226.4673 - val_loss: 1222.7566 - val_mae: 1221.7354
Epoch 24/200
19/19  0s 10ms/step - loss: 1199.7534 - mae: 1198.7269 - val_loss: 1214.1465 - val_mae: 1213.1135
Epoch 25/200
19/19  0s 11ms/step - loss: 1191.6870 - mae: 1190.6575 - val_loss: 1197.4155 - val_mae: 1196.3868
Epoch 26/200
19/19  0s 10ms/step - loss: 1163.6930 - mae: 1162.6599 - val_loss: 1187.9922 - val_mae: 1186.9528
Epoch 27/200
19/19  0s 11ms/step - loss: 1133.7819 - mae: 1132.7415 - val_loss: 1175.4658 - val_mae: 1174.4214
Epoch 28/200
19/19  0s 12ms/step - loss: 1175.3257 - mae: 1174.2802 - val_loss: 1164.2544 - val_mae: 1163.2034
Epoch 29/200
19/19  0s 11ms/step - loss: 1092.8240 - mae: 1091.7742 - val_loss: 1153.0817 - val_mae: 1152.0256
Epoch 30/200
19/19  0s 12ms/step - loss: 1094.7131 - mae: 1093.6541 - val_loss: 1142.0020 - val_mae: 1140.9371
Epoch 31/200
19/19  0s 11ms/step - loss: 1190.6207 - mae: 1189.5547 - val_loss: 1128.6660 - val_mae: 1127.5973
Epoch 32/200
19/19  0s 10ms/step - loss: 1091.8600 - mae: 1090.7896 - val_loss: 1120.4484 - val_mae: 1119.3688
Epoch 33/200
19/19  0s 10ms/step - loss: 1113.0491 - mae: 1111.9634 - val_loss: 1115.1091 - val_mae: 1114.0127
Epoch 34/200
19/19  0s 11ms/step - loss: 1157.3291 - mae: 1156.2310 - val_loss: 1097.5957 - val_mae: 1096.4998
Epoch 35/200
19/19  0s 11ms/step - loss: 1128.8601 - mae: 1127.7654 - val_loss: 1080.9867 - val_mae: 1079.8937
Epoch 36/200
19/19  0s 11ms/step - loss: 1079.4803 - mae: 1078.3879 - val_loss: 1068.7314 - val_mae: 1067.6360
Epoch 37/200
19/19  0s 10ms/step - loss: 1103.8442 - mae: 1102.7440 - val_loss: 1065.9971 - val_mae: 1064.8788
Epoch 38/200
19/19  0s 11ms/step - loss: 1045.9812 - mae: 1044.8619 - val_loss: 1054.3812 - val_mae: 1053.2590
Epoch 39/200
19/19  0s 10ms/step - loss: 1072.0463 - mae: 1070.9226 - val_loss: 1046.5282 - val_mae: 1045.3956
Epoch 40/200
19/19  0s 10ms/step - loss: 1044.8029 - mae: 1043.6721 - val_loss: 1031.5260 - val_mae: 1030.3955
Epoch 41/200
19/19  0s 11ms/step - loss: 1052.9030 - mae: 1051.7655 - val_loss: 1025.6023 - val_mae: 1024.4564
Epoch 42/200
19/19  0s 12ms/step - loss: 1010.1057 - mae: 1008.9586 - val_loss: 1014.2783 - val_mae: 1013.1245
Epoch 43/200
19/19  0s 14ms/step - loss: 1014.5615 - mae: 1013.4042 - val_loss: 1004.8071 - val_mae: 1003.6425
Epoch 44/200
19/19  0s 14ms/step - loss: 969.2139 - mae: 968.0449 - val_loss: 998.2776 - val_mae: 997.1021
Epoch 45/200
19/19  0s 12ms/step - loss: 1007.4569 - mae: 1006.2773 - val_loss: 994.1492 - val_mae: 992.9566
Epoch 46/200
19/19  0s 11ms/step - loss: 1025.3126 - mae: 1024.1157 - val_loss: 991.6988 - val_mae: 990.4872
Epoch 47/200
19/19  0s 11ms/step - loss: 981.9746 - mae: 980.7593 - val_loss: 984.5806 - val_mae: 983.3549
Epoch 48/200
19/19  0s 11ms/step - loss: 1019.2287 - mae: 1018.0016 - val_loss: 970.2419 - val_mae: 969.0118
Epoch 49/200
19/19  0s 11ms/step - loss: 1010.9531 - mae: 1009.7228 - val_loss: 956.9271 - val_mae: 955.6971
Epoch 50/200

19/19 0s 12ms/step - loss: 980.9784 - mae: 979.7475 - val_loss: 950.7380 - val_mae: 949.4948
Epoch 51/200
19/19 0s 15ms/step - loss: 1031.7231 - mae: 1030.4769 - val_loss: 937.4052 - val_mae: 936.1581
Epoch 52/200
19/19 0s 14ms/step - loss: 894.6324 - mae: 893.3806 - val_loss: 931.7916 - val_mae: 930.5258
Epoch 53/200
19/19 0s 11ms/step - loss: 1000.3016 - mae: 999.0344 - val_loss: 922.5634 - val_mae: 921.2903
Epoch 54/200
19/19 0s 11ms/step - loss: 1009.1716 - mae: 1007.8959 - val_loss: 913.1550 - val_mae: 911.8803
Epoch 55/200
19/19 0s 11ms/step - loss: 893.7050 - mae: 892.4298 - val_loss: 907.2089 - val_mae: 905.9171
Epoch 56/200
19/19 0s 11ms/step - loss: 999.7149 - mae: 998.4148 - val_loss: 904.3455 - val_mae: 903.0308
Epoch 57/200
19/19 0s 15ms/step - loss: 921.8631 - mae: 920.5519 - val_loss: 892.1005 - val_mae: 890.7892
Epoch 58/200
19/19 0s 12ms/step - loss: 914.0128 - mae: 912.6995 - val_loss: 883.8745 - val_mae: 882.5594
Epoch 59/200
19/19 0s 11ms/step - loss: 915.5955 - mae: 914.2826 - val_loss: 875.2808 - val_mae: 873.9572
Epoch 60/200
19/19 0s 10ms/step - loss: 916.1359 - mae: 914.8055 - val_loss: 870.2317 - val_mae: 868.8872
Epoch 61/200
19/19 0s 11ms/step - loss: 951.7470 - mae: 950.3992 - val_loss: 863.1848 - val_mae: 861.8292
Epoch 62/200
19/19 0s 10ms/step - loss: 932.6001 - mae: 931.2350 - val_loss: 864.6030 - val_mae: 863.2198
Epoch 63/200
19/19 0s 11ms/step - loss: 915.0896 - mae: 913.7045 - val_loss: 856.9208 - val_mae: 855.5273
Epoch 64/200
19/19 0s 16ms/step - loss: 834.8410 - mae: 833.4461 - val_loss: 842.8105 - val_mae: 841.4250
Epoch 65/200
19/19 0s 12ms/step - loss: 880.2955 - mae: 878.9080 - val_loss: 836.3865 - val_mae: 834.9949
Epoch 66/200
19/19 0s 14ms/step - loss: 884.0200 - mae: 882.6304 - val_loss: 830.0997 - val_mae: 828.7062
Epoch 67/200
19/19 0s 18ms/step - loss: 885.4894 - mae: 884.0880 - val_loss: 826.0927 - val_mae: 824.6773
Epoch 68/200
19/19 0s 13ms/step - loss: 851.9224 - mae: 850.5059 - val_loss: 820.4434 - val_mae: 819.0177
Epoch 69/200
19/19 0s 12ms/step - loss: 871.6196 - mae: 870.1877 - val_loss: 820.1261 - val_mae: 818.6803
Epoch 70/200
19/19 0s 15ms/step - loss: 849.9495 - mae: 848.5019 - val_loss: 809.0763 - val_mae: 807.6277
Epoch 71/200
19/19 0s 11ms/step - loss: 888.4971 - mae: 887.0472 - val_loss: 800.5263 - val_mae: 799.0776
Epoch 72/200
19/19 0s 11ms/step - loss: 812.0151 - mae: 810.5601 - val_loss: 798.4902 - val_mae: 797.0200
Epoch 73/200
19/19 0s 11ms/step - loss: 842.2809 - mae: 840.8118 - val_loss: 790.3657 - val_mae: 788.8942
Epoch 74/200
19/19 0s 13ms/step - loss: 856.0541 - mae: 854.5778 - val_loss: 785.7206 - val_mae: 784.2330
Epoch 75/200
19/19 0s 13ms/step - loss: 867.5366 - mae: 866.0419 - val_loss: 777.9336 - val_mae: 776.4325
Epoch 76/200
19/19 0s 13ms/step - loss: 870.3337 - mae: 868.8318 - val_loss: 770.8046 - val_mae: 769.3053
Epoch 77/200
19/19 0s 11ms/step - loss: 846.2054 - mae: 844.7089 - val_loss: 765.2260 - val_mae: 763.7267
Epoch 78/200
19/19 0s 11ms/step - loss: 789.9863 - mae: 788.4777 - val_loss: 761.6196 - val_mae: 760.0940
Epoch 79/200
19/19 0s 12ms/step - loss: 790.6072 - mae: 789.0780 - val_loss: 759.3185 - val_mae: 757.7740
Epoch 80/200
19/19 0s 12ms/step - loss: 808.2346 - mae: 806.6935 - val_loss: 750.2519 - val_mae: 748.7145
Epoch 81/200
19/19 0s 11ms/step - loss: 789.1612 - mae: 787.6227 - val_loss: 745.6009 - val_mae: 744.0492
Epoch 82/200
19/19 0s 11ms/step - loss: 784.4965 - mae: 782.9407 - val_loss: 742.5627 - val_mae: 740.9971
Epoch 83/200
19/19 0s 13ms/step - loss: 770.6345 - mae: 769.0681 - val_loss: 736.1655 - val_mae: 734.6072
Epoch 84/200
19/19 0s 11ms/step - loss: 824.4052 - mae: 822.8457 - val_loss: 732.1643 - val_mae: 730.5918
Epoch 85/200
19/19 0s 11ms/step - loss: 769.9217 - mae: 768.3508 - val_loss: 726.5209 - val_mae: 724.9515
Epoch 86/200
19/19 0s 11ms/step - loss: 786.1402 - mae: 784.5746 - val_loss: 721.7018 - val_mae: 720.1298
Epoch 87/200
19/19 0s 11ms/step - loss: 793.3354 - mae: 791.7620 - val_loss: 716.4293 - val_mae: 714.8492
Epoch 88/200
19/19 0s 11ms/step - loss: 804.3647 - mae: 802.7856 - val_loss: 712.4064 - val_mae: 710.8151
Epoch 89/200
19/19 0s 11ms/step - loss: 791.1126 - mae: 789.5119 - val_loss: 710.9776 - val_mae: 709.3616
Epoch 90/200
19/19 0s 11ms/step - loss: 773.7646 - mae: 772.1461 - val_loss: 705.1160 - val_mae: 703.4990
Epoch 91/200
19/19 0s 11ms/step - loss: 814.1959 - mae: 812.5817 - val_loss: 700.0049 - val_mae: 698.3878
Epoch 92/200
19/19 0s 11ms/step - loss: 788.6415 - mae: 787.0166 - val_loss: 697.3349 - val_mae: 695.6993
Epoch 93/200
19/19 0s 11ms/step - loss: 790.9146 - mae: 789.2822 - val_loss: 691.1297 - val_mae: 689.5057
Epoch 94/200
19/19 0s 11ms/step - loss: 767.9291 - mae: 766.3029 - val_loss: 687.2001 - val_mae: 685.5624
Epoch 95/200
19/19 0s 13ms/step - loss: 774.8090 - mae: 773.1669 - val_loss: 684.4249 - val_mae: 682.7702
Epoch 96/200
19/19 0s 10ms/step - loss: 750.2581 - mae: 748.6010 - val_loss: 680.9288 - val_mae: 679.2704
Epoch 97/200
19/19 0s 12ms/step - loss: 784.3438 - mae: 782.6826 - val_loss: 676.5655 - val_mae: 674.9005
Epoch 98/200
19/19 0s 10ms/step - loss: 744.9326 - mae: 743.2654 - val_loss: 676.3279 - val_mae: 674.6467
Epoch 99/200
19/19 0s 11ms/step - loss: 737.2904 - mae: 735.6089 - val_loss: 671.4297 - val_mae: 669.7484

Epoch 100/200
19/19  0s 10ms/step - loss: 712.7378 - mae: 711.0519 - val_loss: 665.6396 - val_mae: 663.9506
Epoch 101/200
19/19  0s 10ms/step - loss: 732.6462 - mae: 730.9648 - val_loss: 661.7282 - val_mae: 660.0479
Epoch 102/200
19/19  0s 10ms/step - loss: 773.6191 - mae: 771.9388 - val_loss: 658.5701 - val_mae: 656.8748
Epoch 103/200
19/19  0s 10ms/step - loss: 751.6774 - mae: 749.9780 - val_loss: 661.4739 - val_mae: 659.7553
Epoch 104/200
19/19  0s 10ms/step - loss: 736.8128 - mae: 735.0839 - val_loss: 659.6986 - val_mae: 657.9676
Epoch 105/200
19/19  0s 10ms/step - loss: 779.6933 - mae: 777.9708 - val_loss: 649.2672 - val_mae: 647.5597
Epoch 106/200
19/19  0s 12ms/step - loss: 793.7404 - mae: 792.0289 - val_loss: 647.7982 - val_mae: 646.0751
Epoch 107/200
19/19  0s 11ms/step - loss: 691.0097 - mae: 689.2841 - val_loss: 646.9017 - val_mae: 645.1667
Epoch 108/200
19/19  0s 10ms/step - loss: 732.1285 - mae: 730.3917 - val_loss: 644.1617 - val_mae: 642.4154
Epoch 109/200
19/19  0s 10ms/step - loss: 719.1222 - mae: 717.3734 - val_loss: 640.2694 - val_mae: 638.5188
Epoch 110/200
19/19  0s 11ms/step - loss: 732.8746 - mae: 731.1222 - val_loss: 639.1129 - val_mae: 637.3526
Epoch 111/200
19/19  0s 10ms/step - loss: 748.4610 - mae: 746.7000 - val_loss: 636.3787 - val_mae: 634.6182
Epoch 112/200
19/19  0s 10ms/step - loss: 672.4647 - mae: 670.7070 - val_loss: 632.7331 - val_mae: 630.9800
Epoch 113/200
19/19  0s 10ms/step - loss: 730.5534 - mae: 728.7984 - val_loss: 630.3253 - val_mae: 628.5670
Epoch 114/200
19/19  0s 11ms/step - loss: 749.1071 - mae: 747.3446 - val_loss: 627.0785 - val_mae: 625.3110
Epoch 115/200
19/19  0s 10ms/step - loss: 686.9233 - mae: 685.1538 - val_loss: 626.0933 - val_mae: 624.3142
Epoch 116/200
19/19  0s 10ms/step - loss: 784.8356 - mae: 783.0544 - val_loss: 621.3120 - val_mae: 619.5287
Epoch 117/200
19/19  0s 10ms/step - loss: 708.5501 - mae: 706.7692 - val_loss: 616.9731 - val_mae: 615.1953
Epoch 118/200
19/19  0s 10ms/step - loss: 689.4962 - mae: 687.7197 - val_loss: 614.5931 - val_mae: 612.8061
Epoch 119/200
19/19  0s 10ms/step - loss: 708.9326 - mae: 707.1393 - val_loss: 613.2834 - val_mae: 611.4910
Epoch 120/200
19/19  0s 11ms/step - loss: 801.6440 - mae: 799.8536 - val_loss: 609.9542 - val_mae: 608.1603
Epoch 121/200
19/19  0s 11ms/step - loss: 737.3420 - mae: 735.5477 - val_loss: 609.0213 - val_mae: 607.2320
Epoch 122/200
19/19  0s 10ms/step - loss: 736.4358 - mae: 734.6459 - val_loss: 606.9373 - val_mae: 605.1398
Epoch 123/200
19/19  0s 11ms/step - loss: 673.1745 - mae: 671.3762 - val_loss: 604.1174 - val_mae: 602.3099
Epoch 124/200
19/19  0s 10ms/step - loss: 816.7501 - mae: 814.9361 - val_loss: 601.1227 - val_mae: 599.3088
Epoch 125/200
19/19  0s 13ms/step - loss: 743.2733 - mae: 741.4628 - val_loss: 600.0262 - val_mae: 598.2144
Epoch 126/200
19/19  0s 11ms/step - loss: 679.2260 - mae: 677.4140 - val_loss: 598.2781 - val_mae: 596.4622
Epoch 127/200
19/19  0s 11ms/step - loss: 694.7672 - mae: 692.9477 - val_loss: 597.6536 - val_mae: 595.8292
Epoch 128/200
19/19  0s 11ms/step - loss: 711.5659 - mae: 709.7414 - val_loss: 595.9468 - val_mae: 594.1248
Epoch 129/200
19/19  0s 11ms/step - loss: 684.8705 - mae: 683.0526 - val_loss: 596.5620 - val_mae: 594.7418
Epoch 130/200
19/19  0s 10ms/step - loss: 720.1461 - mae: 718.3300 - val_loss: 597.0337 - val_mae: 595.2207
Epoch 131/200
19/19  0s 10ms/step - loss: 699.5649 - mae: 697.7485 - val_loss: 592.2815 - val_mae: 590.4503
Epoch 132/200
19/19  0s 10ms/step - loss: 683.9081 - mae: 682.0774 - val_loss: 591.4644 - val_mae: 589.6363
Epoch 133/200
19/19  0s 10ms/step - loss: 747.9731 - mae: 746.1432 - val_loss: 591.4791 - val_mae: 589.6484
Epoch 134/200
19/19  0s 11ms/step - loss: 683.2073 - mae: 681.3822 - val_loss: 592.1057 - val_mae: 590.2889
Epoch 135/200
19/19  0s 11ms/step - loss: 753.3751 - mae: 751.5542 - val_loss: 587.7170 - val_mae: 585.8857
Epoch 136/200
19/19  0s 13ms/step - loss: 678.1646 - mae: 676.3335 - val_loss: 586.3719 - val_mae: 584.5397
Epoch 137/200
19/19  0s 11ms/step - loss: 717.8802 - mae: 716.0402 - val_loss: 586.2073 - val_mae: 584.3564
Epoch 138/200
19/19  0s 11ms/step - loss: 705.1950 - mae: 703.3438 - val_loss: 583.8627 - val_mae: 582.0122
Epoch 139/200
19/19  0s 11ms/step - loss: 760.5809 - mae: 758.7274 - val_loss: 581.9326 - val_mae: 580.0825
Epoch 140/200
19/19  0s 11ms/step - loss: 696.3617 - mae: 694.5148 - val_loss: 580.5589 - val_mae: 578.7143
Epoch 141/200
19/19  0s 10ms/step - loss: 684.6011 - mae: 682.7586 - val_loss: 582.0964 - val_mae: 580.2526
Epoch 142/200
19/19  0s 11ms/step - loss: 743.7766 - mae: 741.9254 - val_loss: 581.5604 - val_mae: 579.6892
Epoch 143/200
19/19  0s 10ms/step - loss: 716.2654 - mae: 714.3937 - val_loss: 580.7333 - val_mae: 578.8645
Epoch 144/200
19/19  0s 12ms/step - loss: 690.2793 - mae: 688.4106 - val_loss: 580.2809 - val_mae: 578.4050
Epoch 145/200
19/19  0s 10ms/step - loss: 688.5627 - mae: 686.6842 - val_loss: 578.2496 - val_mae: 576.3781
Epoch 146/200
19/19  0s 10ms/step - loss: 751.8508 - mae: 749.9822 - val_loss: 576.9910 - val_mae: 575.1272
Epoch 147/200
19/19  0s 12ms/step - loss: 718.7983 - mae: 716.9357 - val_loss: 576.4542 - val_mae: 574.5833
Epoch 148/200
19/19  0s 11ms/step - loss: 669.3762 - mae: 667.4992 - val_loss: 575.5751 - val_mae: 573.6985
Epoch 149/200

19/19 0s 11ms/step - loss: 652.2554 - mae: 650.3860 - val_loss: 576.4547 - val_mae: 574.5945
Epoch 150/200
19/19 0s 11ms/step - loss: 685.2943 - mae: 683.4323 - val_loss: 570.9798 - val_mae: 569.1100
Epoch 151/200
19/19 0s 10ms/step - loss: 713.6679 - mae: 711.7969 - val_loss: 571.5530 - val_mae: 569.6773
Epoch 152/200
19/19 0s 11ms/step - loss: 722.2767 - mae: 720.3962 - val_loss: 570.2697 - val_mae: 568.3923
Epoch 153/200
19/19 0s 13ms/step - loss: 706.5213 - mae: 704.6470 - val_loss: 574.1412 - val_mae: 572.2742
Epoch 154/200
19/19 0s 10ms/step - loss: 711.6840 - mae: 709.8127 - val_loss: 565.6605 - val_mae: 563.7749
Epoch 155/200
19/19 0s 10ms/step - loss: 668.4133 - mae: 666.5223 - val_loss: 564.1684 - val_mae: 562.2755
Epoch 156/200
19/19 0s 10ms/step - loss: 721.2075 - mae: 719.3198 - val_loss: 566.4645 - val_mae: 564.5804
Epoch 157/200
19/19 0s 10ms/step - loss: 697.4852 - mae: 695.5988 - val_loss: 562.5220 - val_mae: 560.6224
Epoch 158/200
19/19 0s 10ms/step - loss: 737.1700 - mae: 735.2762 - val_loss: 565.4833 - val_mae: 563.5964
Epoch 159/200
19/19 0s 12ms/step - loss: 671.6415 - mae: 669.7530 - val_loss: 560.2587 - val_mae: 558.3592
Epoch 160/200
19/19 0s 14ms/step - loss: 721.0084 - mae: 719.1092 - val_loss: 560.6699 - val_mae: 558.7776
Epoch 161/200
19/19 0s 11ms/step - loss: 738.3420 - mae: 736.4520 - val_loss: 559.5146 - val_mae: 557.6228
Epoch 162/200
19/19 0s 11ms/step - loss: 736.4139 - mae: 734.5165 - val_loss: 559.3220 - val_mae: 557.4229
Epoch 163/200
19/19 0s 10ms/step - loss: 727.7090 - mae: 725.8076 - val_loss: 558.5740 - val_mae: 556.6680
Epoch 164/200
19/19 0s 12ms/step - loss: 678.8569 - mae: 676.9521 - val_loss: 556.0460 - val_mae: 554.1417
Epoch 165/200
19/19 0s 11ms/step - loss: 664.7240 - mae: 662.8243 - val_loss: 554.7980 - val_mae: 552.8992
Epoch 166/200
19/19 0s 12ms/step - loss: 715.9023 - mae: 713.9960 - val_loss: 554.3733 - val_mae: 552.4568
Epoch 167/200
19/19 0s 13ms/step - loss: 679.3464 - mae: 677.4346 - val_loss: 554.9496 - val_mae: 553.0413
Epoch 168/200
19/19 0s 10ms/step - loss: 691.7283 - mae: 689.8228 - val_loss: 554.4753 - val_mae: 552.5657
Epoch 169/200
19/19 0s 11ms/step - loss: 671.5981 - mae: 669.6866 - val_loss: 553.3322 - val_mae: 551.4032
Epoch 170/200
19/19 0s 14ms/step - loss: 659.2076 - mae: 657.2792 - val_loss: 552.3633 - val_mae: 550.4450
Epoch 171/200
19/19 0s 11ms/step - loss: 685.8631 - mae: 683.9487 - val_loss: 559.3513 - val_mae: 557.4465
Epoch 172/200
19/19 0s 11ms/step - loss: 725.3423 - mae: 723.4406 - val_loss: 552.9328 - val_mae: 551.0123
Epoch 173/200
19/19 0s 13ms/step - loss: 687.3757 - mae: 685.4547 - val_loss: 556.0584 - val_mae: 554.1424
Epoch 174/200
19/19 0s 10ms/step - loss: 706.2889 - mae: 704.3682 - val_loss: 552.2267 - val_mae: 550.2992
Epoch 175/200
19/19 0s 10ms/step - loss: 696.3327 - mae: 694.3990 - val_loss: 550.6264 - val_mae: 548.6902
Epoch 176/200
19/19 0s 13ms/step - loss: 702.5817 - mae: 700.6545 - val_loss: 551.7636 - val_mae: 549.8385
Epoch 177/200
19/19 0s 10ms/step - loss: 684.9595 - mae: 683.0284 - val_loss: 547.8101 - val_mae: 545.8687
Epoch 178/200
19/19 0s 11ms/step - loss: 655.2465 - mae: 653.3071 - val_loss: 549.1832 - val_mae: 547.2509
Epoch 179/200
19/19 0s 13ms/step - loss: 678.7722 - mae: 676.8373 - val_loss: 546.2778 - val_mae: 544.3294
Epoch 180/200
19/19 0s 11ms/step - loss: 678.0178 - mae: 676.0709 - val_loss: 544.6198 - val_mae: 542.6762
Epoch 181/200
19/19 0s 11ms/step - loss: 714.5034 - mae: 712.5563 - val_loss: 542.2024 - val_mae: 540.2589
Epoch 182/200
19/19 0s 12ms/step - loss: 688.6781 - mae: 686.7413 - val_loss: 550.4717 - val_mae: 548.5483
Epoch 183/200
19/19 0s 11ms/step - loss: 700.1882 - mae: 698.2698 - val_loss: 550.9188 - val_mae: 548.9977
Epoch 184/200
19/19 0s 11ms/step - loss: 679.0678 - mae: 677.1389 - val_loss: 542.6270 - val_mae: 540.6839
Epoch 185/200
19/19 0s 13ms/step - loss: 653.4854 - mae: 651.5441 - val_loss: 544.1950 - val_mae: 542.2689
Epoch 186/200
19/19 0s 14ms/step - loss: 644.9713 - mae: 643.0461 - val_loss: 544.8267 - val_mae: 542.9012
Epoch 187/200
19/19 0s 12ms/step - loss: 705.8246 - mae: 703.8985 - val_loss: 542.9344 - val_mae: 541.0025
Epoch 188/200
19/19 0s 14ms/step - loss: 683.7574 - mae: 681.8185 - val_loss: 542.2756 - val_mae: 540.3234
Epoch 189/200
19/19 0s 11ms/step - loss: 754.9102 - mae: 752.9594 - val_loss: 540.2831 - val_mae: 538.3356
Epoch 190/200
19/19 0s 11ms/step - loss: 656.4404 - mae: 654.4950 - val_loss: 543.1083 - val_mae: 541.1672
Epoch 191/200
19/19 0s 12ms/step - loss: 660.8201 - mae: 658.8809 - val_loss: 542.2528 - val_mae: 540.3097
Epoch 192/200
19/19 0s 11ms/step - loss: 690.1031 - mae: 688.1613 - val_loss: 541.1152 - val_mae: 539.1716
Epoch 193/200
19/19 0s 11ms/step - loss: 675.2617 - mae: 673.3140 - val_loss: 540.4325 - val_mae: 538.4874
Epoch 194/200
19/19 0s 11ms/step - loss: 757.2009 - mae: 755.2590 - val_loss: 544.8805 - val_mae: 542.9426
Epoch 195/200
19/19 0s 11ms/step - loss: 667.1857 - mae: 665.2492 - val_loss: 539.4807 - val_mae: 537.5345
Epoch 196/200
19/19 0s 11ms/step - loss: 659.0410 - mae: 657.0880 - val_loss: 540.2381 - val_mae: 538.2934
Epoch 197/200
19/19 0s 11ms/step - loss: 693.0178 - mae: 691.0775 - val_loss: 545.6274 - val_mae: 543.6924
Epoch 198/200
19/19 0s 13ms/step - loss: 702.0306 - mae: 700.0934 - val_loss: 541.1767 - val_mae: 539.2336

```
Epoch 199/200
19/19 ————— 0s 11ms/step - loss: 685.0792 - mae: 683.1321 - val_loss: 535.2029 - val_mae: 533.2411
Epoch 200/200
19/19 ————— 0s 11ms/step - loss: 710.7750 - mae: 708.8141 - val_loss: 536.0221 - val_mae: 534.0678
```

```
In [29]: # Predict
y_pred_nn = model.predict(X_test_processed).flatten()
y_pred_nn_train = model.predict(X_train_processed).flatten()
```

```
5/5 ————— 0s 33ms/step
19/19 ————— 0s 4ms/step
```

```
In [30]: # Random Forest model
rf = RandomForestRegressor(random_state=42)
rf.fit(X_train, y_train)
y_pred_rf = rf.predict(X_test)
y_pred_rf_train = rf.predict(X_train)
```

```
In [31]: # Ensemble predictions
y_pred_ensemble = 0.5 * y_pred_nn + 0.5 * y_pred_rf
y_pred_ensemble_train = 0.5 * y_pred_nn_train + 0.5 * y_pred_rf_train
```

```
In [32]: # Evaluation
print("\n--- Train Data ---")
print("NN MAE:", mean_absolute_error(y_train, y_pred_nn_train))
print("RF MAE:", mean_absolute_error(y_train, y_pred_rf_train))
print("Ensemble MAE:", mean_absolute_error(y_train, y_pred_ensemble_train))
print("Ensemble R²:", r2_score(y_train, y_pred_ensemble_train))

print("\n--- Test Data ---")
print("NN MAE:", mean_absolute_error(y_test, y_pred_nn))
print("RF MAE:", mean_absolute_error(y_test, y_pred_rf))
print("Ensemble MAE:", mean_absolute_error(y_test, y_pred_ensemble))
print("Ensemble R²:", r2_score(y_test, y_pred_ensemble))
```

```
--- Train Data ---
NN MAE: 487.3140102151322
RF MAE: 156.31785958904112
Ensemble MAE: 305.327318936962
Ensemble R²: 0.950593482998715
```

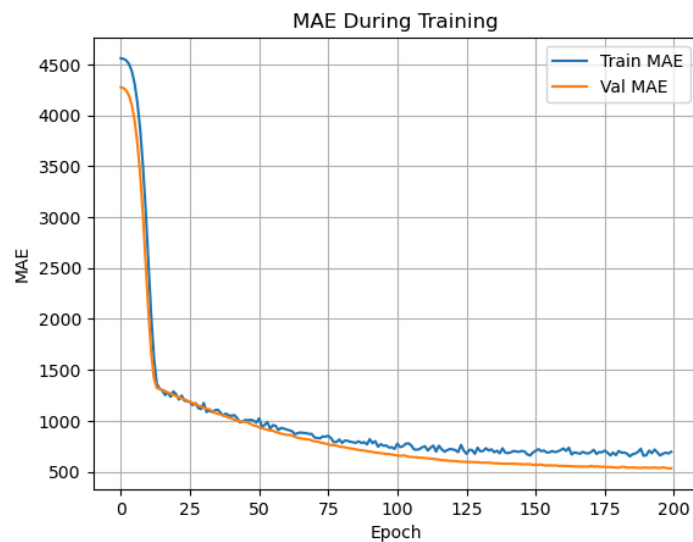
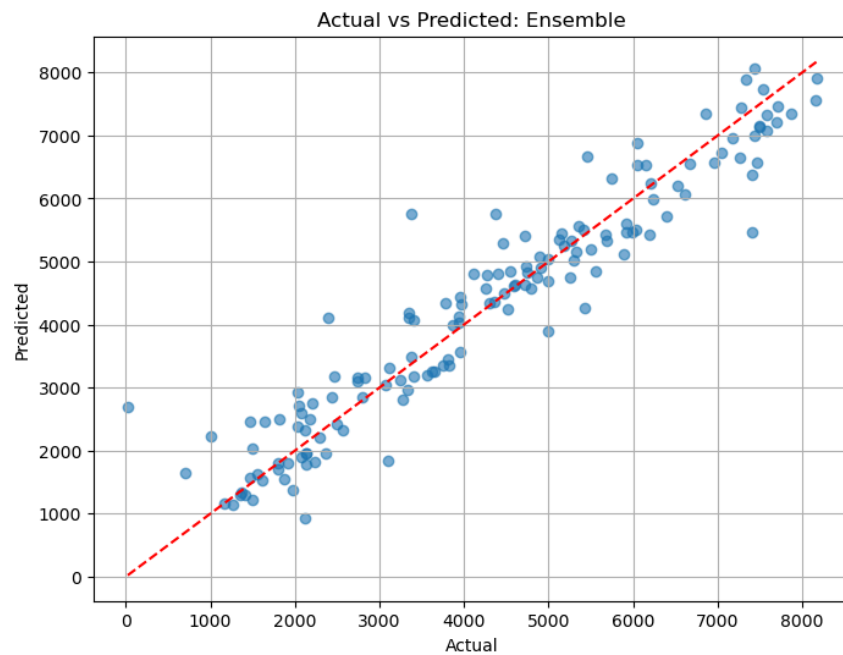
```
--- Test Data ---
NN MAE: 533.2410564811862
RF MAE: 423.8632653061224
Ensemble MAE: 445.1483406077274
Ensemble R²: 0.9062479615075307
```

```
In [33]: # Save and Load model
model.save("bike_model_final.h5")
# model = load_model("bike_model_final.h5", custom_objects={'Huber': Huber()})
```

WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')` or `keras.saving.save_model(model, 'my_model.keras')`.

```
In [34]: # Plot results
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_ensemble, alpha=0.6)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Actual vs Predicted: Ensemble")
plt.grid(True)
plt.show()

plt.plot(history.history['mae'], label='Train MAE')
plt.plot(history.history['val_mae'], label='Val MAE')
plt.xlabel("Epoch")
plt.ylabel("MAE")
plt.title("MAE During Training")
plt.legend()
plt.grid(True)
plt.show()
```



```
In [35]: # Predict on training data
y_pred_nn_train = model.predict(X_train_processed).flatten()
y_pred_rf_train = rf.predict(X_train)
y_pred_ensemble_train = 0.5 * y_pred_nn_train + 0.5 * y_pred_rf_train

print("--- Evaluation on Training Data ---")
print("Neural Network Train MAE:", mean_absolute_error(y_train, y_pred_nn_train))
print("Random Forest Train MAE:", mean_absolute_error(y_train, y_pred_rf_train))
print("Ensemble Train MAE:", mean_absolute_error(y_train, y_pred_ensemble_train))
print("Ensemble Train R² Score:", r2_score(y_train, y_pred_ensemble_train))

19/19 ————— 0s 4ms/step
--- Evaluation on Training Data ---
Neural Network Train MAE: 487.3140102151322
Random Forest Train MAE: 156.31785958904112
Ensemble Train MAE: 305.327318936962
Ensemble Train R² Score: 0.950593482998715
```