University Building ANN Model

November 23, 2020

```
[120]: # import the libraries
       import numpy as np
       import matplotlib.pyplot as plt
       import datetime
       import seaborn as sns
       import tensorflow as tf
       import pandas as pd
       from datetime import datetime
       print("TensorFlow version: ",tf.__version__) #print the version of tensorflow
      TensorFlow version: 2.3.0
[121]: from tensorflow.python.keras.layers import Dense
       from tensorflow.keras.layers import Dropout
       from tensorflow.python.keras.models import Sequential
       from tensorflow.python.keras.wrappers.scikit_learn import KerasRegressor
       from tensorflow import keras
       from tensorflow.keras import layers
       from tensorflow.keras import Sequential
       from tensorflow.keras.layers import Dense, Activation, Dropout
       from tensorflow.keras.callbacks import EarlyStopping
       from tensorflow.keras import regularizers
       from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
       from tensorflow.keras import regularizers
[122]: #Helper Functions
       def get_weekday2(year, month, day):
           dates = pd.DataFrame()
           dates['y'] = year
           dates['m'] = month
           dates['d'] = day
           dates['dates'] = dates['y'].astype('str') + '-' + dates['m'].astype('str')__
       →+ '-' + dates['d'].astype('str')
           return get_weekday(dates['dates'])
       #Get day of week based on date
       def get_weekday(dates):
```

```
return [1 if (datetime.strptime(d,"%Y-%m-%d").weekday() >= 5) else 0 for d_ \cup in dates]
```

1 Exploratory Data Analysis

```
[123]: data = pd.read_csv('https://raw.githubusercontent.com/A-Wadhwani/ME597-Project/
        →main/Datasets/Combined_PowerWeatherData.csv')
       copy = data
       data
[123]:
              Year
                    Month
                               Square Feet
                                                         Type
              2019
                         1
                                    113866
                                            College Building
       1
              2019
                         1
                                           College Building
                                    113866
       2
              2019
                         1
                                    113866
                                            College Building
                                            College Building
       3
              2019
                         1
                                    113866
                                            College Building
       4
              2019
                                    113866
       21179
             2019
                        12
                                    135129
                                                   Laboratory
       21180 2019
                        12
                                    135129
                                                   Laboratory
       21181
              2019
                        12
                                                   Laboratory
                                    135129
                        12
       21182
              2019
                                                   Laboratory
                                    135129
       21183
             2019
                        12
                                    135129
                                                   Laboratory
       [21184 rows x 18 columns]
[124]: data.describe()
[124]:
                 Year
                                              Weekday
                                                          Square Feet
                               Month
              21184.0
                        21184.000000
                                         21184.000000
                                                         21184.000000
       count
                                                         99734.046969
               2019.0
                            6.524264
                                              0.284838
       mean
                            3.449431
       std
                  0.0
                                              0.451348
                                                         42419.512278
       min
               2019.0
                            1.000000
                                              0.000000
                                                         10932.000000
       25%
               2019.0
                            4.000000
                                              0.000000
                                                         57714.000000
       50%
               2019.0
                            7.000000
                                              0.000000
                                                        111891.000000
       75%
               2019.0
                           10.000000
                                              1.000000
                                                        131464.000000
       max
               2019.0
                           12.000000
                                              1.000000
                                                        421939.000000
       [8 rows x 15 columns]
[125]: #Creating column to denote each building type
       from sklearn.preprocessing import OrdinalEncoder
       encoder = OrdinalEncoder()
       data['Type'] = encoder.fit_transform(np.reshape(data['Type'].values, (-1,1)))
       data['Type'].describe()
```

```
[125]: count
                21184.000000
                    1.758403
      mean
                    0.726795
       std
      min
                    0.000000
       25%
                    2.000000
       50%
                    2.000000
       75%
                    2.000000
                    3.000000
       max
       Name: Type, dtype: float64
[126]: encoder.inverse_transform(np.reshape([0, 1], (-1,1)))
[126]: array([['College Building'],
              ['Facility']], dtype=object)
[127]: #Removing unnecessary columns
       data = data.drop(['Year'], axis=1)
       data = data.drop(['University Name', 'Building Name'], axis=1)
       data.head()
[127]:
          Month Day
                                     Weekday
                                               Square Feet
                        DNI Mean
                                                            Type
                      576.363636
                                                             0.0
       0
              1
                   1
                                            0
                                                    113866
                      576.363636
                                            0
                                                    113866
                                                             0.0
       1
              1
       2
                   2 349.636364
                                            0
                                                    113866
                                                             0.0
              1
       3
                      262.818182 ...
                                            0
                                                             0.0
              1
                                                    113866
                      316.000000 ...
                                                    113866
                                                             0.0
       [5 rows x 15 columns]
[128]: #Select one building's data
       view = data[data['Square Feet'] == 113866]
       #See graphs for data vs Power Consumption
       sns.pairplot(view, x_vars = ['DNI Mean', 'Precipitable Water', 'Relative_
        →Humidity', 'Temperature', 'Pressure', 'Wind Speed'], y_vars=['Power_
        plt.show()
           E 10000
            8000
            6000
```

```
[129]: #Splitting into X and Y
      X = data.drop(["Power Consumption"],axis=1)
      y = data["Power Consumption"]
[130]: y = np.reshape(y.values, (-1,1))
[131]: # scaling inputs using RobustScaler
      from sklearn.preprocessing import RobustScaler
      x_scaler = RobustScaler()
      y_scaler = RobustScaler()
      x_f = x_scaler.fit_transform(X)
      y_f = y_scaler.fit_transform(y)
      x_f = pd.DataFrame(x_f)
[132]: x_f
[132]:
                   0
                                                              10
                                                                   11
                                                                             12
                                                                                  13
            -1.000000 -1.000000 -0.008079 -0.259615
                                                    ... 2.367305 0.0 0.026780 -2.0
            -1.000000 -1.000000 -0.008079 -0.259615 ... 2.367305 0.0 0.026780 -2.0
      1
      2
            -1.000000 -0.933333 -0.537107 -0.264423
                                                     ... 2.377706 0.0 0.026780 -2.0
      3
            -1.000000 -0.866667 -0.739682 -1.134615 ...
                                                        2.024090 0.0 0.026780 -2.0
            -1.000000 -0.800000 -0.615591 -0.072115 ... 1.597671 0.0 0.026780 -2.0
      21179 0.833333 0.733333 0.049522 -0.072115 ... 0.267972 0.0 0.315092
                                                                                0.0
      21180 0.833333 0.800000 0.190338 0.000000 ... 0.548264 1.0 0.315092
      21181 0.833333 0.866667 -1.263255 -3.860577 ... 0.332529 1.0 0.315092
                                                                                0.0
      21182 0.833333 0.933333 0.201888 -0.096154 ... 0.445300 0.0 0.315092
                                                                                0.0
      21183 0.833333 1.000000 -0.237360 -0.716346 ... 0.531104 0.0 0.315092 0.0
      [21184 rows x 14 columns]
[133]: x_f = x_f.values
[134]: x_f.dtype
[134]: dtype('float64')
[135]: # split the data into train and test sets
      from sklearn.model_selection import train_test_split
      x_f_train, x_f_test, y_f_train, y_f_test = train_test_split(x_f,y_f, test_size_
       →= 0.25, shuffle=True,random_state=24)
[136]: # print the number of training and test damples
      print("Number of training samples: ",len(x_f_train))
      print("Number of testing samples: ",len(x_f_test))
```

Number of training samples: 15888 Number of testing samples: 5296

2 Building the Model

```
[137]: model = Sequential()
     model.add(Dense(512, input_shape=(14, ), activation='relu', name='dense_1'))
     model.add(Dense(256, activation='relu', name='dense_2'))
     model.add(Dense(128, activation='relu', name='dense_3'))
     model.add(Dense(64, activation='relu', name='dense_4'))
     model.add(Dense(32, activation='relu', name='dense_5'))
     model.add(Dense(16, activation='relu', name='dense_6'))
     model.add(Dense(1, activation='linear', name='dense_output'))
     model.summary()
     Model: "sequential_8"
     Layer (type)
                  Output Shape
                                                  Param #
     ______
     dense_1 (Dense)
                             (None, 512)
                                                   7680
     dense_2 (Dense)
                             (None, 256)
                                                  131328
     dense 3 (Dense)
                             (None, 128)
                                                   32896
                             (None, 64)
     dense_4 (Dense)
                                                   8256
                             (None, 32)
     dense_5 (Dense)
                                                   2080
     ______
     dense_6 (Dense)
                            (None, 16)
                                                   528
     dense_output (Dense) (None, 1) 17
     ______
     Total params: 182,785
     Trainable params: 182,785
     Non-trainable params: 0
[138]: opt = keras.optimizers.Adam(learning_rate = 0.001)
     model.compile(loss='mae', optimizer=opt, metrics=['mse', 'mae'])
     #Tensorboard tool callback
     log dir = ''
     \#log\_dir = "logs \setminus fit3 \setminus " + datetime.now().strftime("%M")
```

```
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir,_
 →histogram_freq=1, profile_batch = 100000000)
#Reduce Learning rate on Plateau
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=10, ___
\rightarrowverbose = 1)
#Earlystopping callback
early_stop = EarlyStopping(monitor = 'val_loss', min_delta= 1e-3, patience = 40, __
 →verbose = 1, restore_best_weights=True)
history = model.fit(x_f_train, y_f_train, callbacks = [tensorboard_callback,__
 →early_stop, reduce_lr],
             validation_data=(x_f_test, y_f_test), epochs=400,__
 →batch_size=90, verbose=1)
Epoch 1/400
0.1705 - mae: 0.2894 - val_loss: 0.2408 - val_mse: 0.1451 - val_mae: 0.2408
Epoch 2/400
0.1426 - mae: 0.2330 - val_loss: 0.2237 - val_mse: 0.1392 - val_mae: 0.2237
Epoch 3/400
0.1400 - mae: 0.2243 - val_loss: 0.2204 - val_mse: 0.1431 - val_mae: 0.2204
Epoch 4/400
0.1384 - mae: 0.2188 - val_loss: 0.2243 - val_mse: 0.1395 - val_mae: 0.2243
Epoch 5/400
0.1381 - mae: 0.2146 - val_loss: 0.2230 - val_mse: 0.1393 - val_mae: 0.2230
Epoch 6/400
0.1364 - mae: 0.2115 - val_loss: 0.2209 - val_mse: 0.1411 - val_mae: 0.2209
Epoch 7/400
0.1368 - mae: 0.2105 - val_loss: 0.2073 - val_mse: 0.1286 - val_mae: 0.2073
Epoch 8/400
0.1336 - mae: 0.2037 - val_loss: 0.2037 - val_mse: 0.1323 - val_mae: 0.2037
0.1333 - mae: 0.2001 - val_loss: 0.2034 - val_mse: 0.1352 - val_mae: 0.2034
Epoch 10/400
0.1349 - mae: 0.2023 - val_loss: 0.1976 - val_mse: 0.1271 - val_mae: 0.1976
Epoch 11/400
```

```
0.1283 - mae: 0.1938 - val_loss: 0.1947 - val_mse: 0.1276 - val_mae: 0.1947
Epoch 12/400
0.1274 - mae: 0.1900 - val_loss: 0.1908 - val_mse: 0.1246 - val_mae: 0.1908
Epoch 13/400
0.1278 - mae: 0.1893 - val_loss: 0.1915 - val_mse: 0.1298 - val_mae: 0.1915
Epoch 14/400
0.1281 - mae: 0.1884 - val_loss: 0.1918 - val_mse: 0.1320 - val_mae: 0.1918
0.1284 - mae: 0.1885 - val_loss: 0.1851 - val_mse: 0.1266 - val_mae: 0.1851
Epoch 16/400
0.1228 - mae: 0.1802 - val_loss: 0.1968 - val_mse: 0.1451 - val_mae: 0.1968
Epoch 17/400
0.1279 - mae: 0.1853 - val_loss: 0.1859 - val_mse: 0.1314 - val_mae: 0.1859
0.1278 - mae: 0.1850 - val_loss: 0.1884 - val_mse: 0.1315 - val_mae: 0.1884
Epoch 19/400
0.1232 - mae: 0.1768 - val_loss: 0.1832 - val_mse: 0.1259 - val_mae: 0.1832
Epoch 20/400
0.1229 - mae: 0.1759 - val_loss: 0.1823 - val_mse: 0.1292 - val_mae: 0.1823
Epoch 21/400
0.1250 - mae: 0.1770 - val_loss: 0.1807 - val_mse: 0.1188 - val_mae: 0.1807
Epoch 22/400
0.1228 - mae: 0.1743 - val_loss: 0.1853 - val_mse: 0.1232 - val_mae: 0.1853
Epoch 23/400
0.1214 - mae: 0.1740 - val_loss: 0.1786 - val_mse: 0.1225 - val_mae: 0.1786
Epoch 24/400
0.1194 - mae: 0.1709 - val_loss: 0.1735 - val_mse: 0.1239 - val_mae: 0.1735
Epoch 25/400
0.1221 - mae: 0.1688 - val_loss: 0.1713 - val_mse: 0.1132 - val_mae: 0.1713
Epoch 26/400
0.1172 - mae: 0.1609 - val_loss: 0.1634 - val_mse: 0.1186 - val_mae: 0.1634
Epoch 27/400
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```
0.1181 - mae: 0.1619 - val_loss: 0.1679 - val_mse: 0.1274 - val_mae: 0.1679
Epoch 28/400
0.1129 - mae: 0.1536 - val_loss: 0.1575 - val_mse: 0.1224 - val_mae: 0.1575
Epoch 29/400
0.1149 - mae: 0.1519 - val_loss: 0.1589 - val_mse: 0.1220 - val_mae: 0.1589
Epoch 30/400
0.1127 - mae: 0.1487 - val_loss: 0.1608 - val_mse: 0.1224 - val_mae: 0.1608
Epoch 31/400
0.1117 - mae: 0.1462 - val_loss: 0.1520 - val_mse: 0.1257 - val_mae: 0.1520
Epoch 32/400
0.1142 - mae: 0.1465 - val_loss: 0.1463 - val_mse: 0.1046 - val_mae: 0.1463
Epoch 33/400
0.1090 - mae: 0.1408 - val_loss: 0.1557 - val_mse: 0.1316 - val_mae: 0.1557
Epoch 34/400
0.1094 - mae: 0.1393 - val_loss: 0.1462 - val_mse: 0.1100 - val_mae: 0.1462
Epoch 35/400
0.1114 - mae: 0.1432 - val_loss: 0.1481 - val_mse: 0.1143 - val_mae: 0.1481
Epoch 36/400
0.1093 - mae: 0.1359 - val_loss: 0.1438 - val_mse: 0.1275 - val_mae: 0.1438
Epoch 37/400
0.1089 - mae: 0.1333 - val_loss: 0.1469 - val_mse: 0.1139 - val_mae: 0.1469
Epoch 38/400
0.1066 - mae: 0.1294 - val loss: 0.1334 - val mse: 0.1068 - val mae: 0.1334
Epoch 39/400
0.1085 - mae: 0.1340 - val_loss: 0.1494 - val_mse: 0.1295 - val_mae: 0.1494
Epoch 40/400
0.1027 - mae: 0.1300 - val_loss: 0.1332 - val_mse: 0.1050 - val_mae: 0.1332
Epoch 41/400
0.1006 - mae: 0.1273 - val_loss: 0.1310 - val_mse: 0.1043 - val_mae: 0.1310
Epoch 42/400
0.1002 - mae: 0.1262 - val_loss: 0.1375 - val_mse: 0.0983 - val_mae: 0.1375
Epoch 43/400
```

```
0.1003 - mae: 0.1299 - val_loss: 0.1250 - val_mse: 0.1035 - val_mae: 0.1250
Epoch 44/400
0.0979 - mae: 0.1241 - val_loss: 0.1286 - val_mse: 0.0988 - val_mae: 0.1286
Epoch 45/400
0.0900 - mae: 0.1196 - val_loss: 0.1174 - val_mse: 0.0875 - val_mae: 0.1174
Epoch 46/400
0.0798 - mae: 0.1158 - val_loss: 0.1234 - val_mse: 0.0858 - val_mae: 0.1234
Epoch 47/400
0.0864 - mae: 0.1197 - val_loss: 0.1187 - val_mse: 0.1114 - val_mae: 0.1187
Epoch 48/400
0.0725 - mae: 0.1072 - val_loss: 0.1081 - val_mse: 0.0857 - val_mae: 0.1081
Epoch 49/400
0.0781 - mae: 0.1056 - val_loss: 0.1253 - val_mse: 0.0950 - val_mae: 0.1253
Epoch 50/400
0.0699 - mae: 0.0982 - val_loss: 0.0990 - val_mse: 0.0706 - val_mae: 0.0990
Epoch 51/400
0.0732 - mae: 0.0986 - val_loss: 0.0969 - val_mse: 0.0651 - val_mae: 0.0969
Epoch 52/400
0.0710 - mae: 0.0931 - val_loss: 0.1103 - val_mse: 0.0942 - val_mae: 0.1103
Epoch 53/400
0.0711 - mae: 0.0940 - val_loss: 0.1055 - val_mse: 0.0880 - val_mae: 0.1055
Epoch 54/400
0.0680 - mae: 0.0888 - val_loss: 0.1208 - val_mse: 0.0928 - val_mae: 0.1208
Epoch 55/400
0.0577 - mae: 0.0839 - val_loss: 0.0924 - val_mse: 0.0651 - val_mae: 0.0924
Epoch 56/400
0.0574 - mae: 0.0815 - val_loss: 0.1097 - val_mse: 0.1027 - val_mae: 0.1097
Epoch 57/400
0.0557 - mae: 0.0826 - val_loss: 0.0999 - val_mse: 0.0786 - val_mae: 0.0999
Epoch 58/400
0.0592 - mae: 0.0812 - val_loss: 0.0864 - val_mse: 0.0672 - val_mae: 0.0864
Epoch 59/400
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```
0.0700 - mae: 0.0884 - val_loss: 0.1109 - val_mse: 0.1011 - val_mae: 0.1109
Epoch 60/400
0.0603 - mae: 0.0810 - val_loss: 0.1054 - val_mse: 0.0840 - val_mae: 0.1054
Epoch 61/400
0.0493 - mae: 0.0706 - val_loss: 0.0850 - val_mse: 0.0664 - val_mae: 0.0850
Epoch 62/400
0.0574 - mae: 0.0768 - val_loss: 0.0765 - val_mse: 0.0551 - val_mae: 0.0765
0.0535 - mae: 0.0746 - val_loss: 0.0869 - val_mse: 0.0454 - val_mae: 0.0869
Epoch 64/400
0.0629 - mae: 0.0863 - val_loss: 0.0822 - val_mse: 0.0572 - val_mae: 0.0822
Epoch 65/400
0.0556 - mae: 0.0764 - val_loss: 0.0746 - val_mse: 0.0434 - val_mae: 0.0746
Epoch 66/400
0.0588 - mae: 0.0758 - val_loss: 0.0958 - val_mse: 0.0891 - val_mae: 0.0958
Epoch 67/400
0.0381 - mae: 0.0605 - val_loss: 0.0605 - val_mse: 0.0308 - val_mae: 0.0605
Epoch 68/400
0.0315 - mae: 0.0545 - val_loss: 0.0730 - val_mse: 0.0551 - val_mae: 0.0730
Epoch 69/400
0.0350 - mae: 0.0571 - val_loss: 0.0556 - val_mse: 0.0275 - val_mae: 0.0556
Epoch 70/400
0.0291 - mae: 0.0540 - val_loss: 0.0544 - val_mse: 0.0263 - val_mae: 0.0544
Epoch 71/400
0.0420 - mae: 0.0625 - val_loss: 0.0639 - val_mse: 0.0417 - val_mae: 0.0639
Epoch 72/400
0.0376 - mae: 0.0594 - val_loss: 0.0599 - val_mse: 0.0324 - val_mae: 0.0599
Epoch 73/400
0.0384 - mae: 0.0616 - val_loss: 0.0600 - val_mse: 0.0367 - val_mae: 0.0600
Epoch 74/400
0.0643 - mae: 0.0777 - val_loss: 0.0637 - val_mse: 0.0442 - val_mae: 0.0637
Epoch 75/400
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```
0.0452 - mae: 0.0623 - val_loss: 0.0815 - val_mse: 0.0760 - val_mae: 0.0815
Epoch 76/400
0.0444 - mae: 0.0640 - val_loss: 0.0788 - val_mse: 0.0614 - val_mae: 0.0788
Epoch 77/400
0.0400 - mae: 0.0579 - val_loss: 0.0703 - val_mse: 0.0576 - val_mae: 0.0703
Epoch 78/400
0.0520 - mae: 0.0660 - val_loss: 0.0793 - val_mse: 0.0716 - val_mae: 0.0793
Epoch 79/400
0.0336 - mae: 0.0522 - val_loss: 0.0882 - val_mse: 0.0798 - val_mae: 0.0882
Epoch 80/400
- mae: 0.0599
Epoch 00080: ReduceLROnPlateau reducing learning rate to 0.00020000000949949026.
0.0415 - mae: 0.0599 - val_loss: 0.0708 - val_mse: 0.0610 - val_mae: 0.0708
Epoch 81/400
0.0092 - mae: 0.0272 - val_loss: 0.0284 - val_mse: 0.0069 - val_mae: 0.0284
Epoch 82/400
0.0027 - mae: 0.0200 - val_loss: 0.0266 - val_mse: 0.0058 - val_mae: 0.0266
Epoch 83/400
0.0022 - mae: 0.0186 - val_loss: 0.0264 - val_mse: 0.0056 - val_mae: 0.0264
Epoch 84/400
0.0020 - mae: 0.0178 - val_loss: 0.0259 - val_mse: 0.0055 - val_mae: 0.0259
Epoch 85/400
0.0018 - mae: 0.0173 - val loss: 0.0250 - val mse: 0.0047 - val mae: 0.0250
Epoch 86/400
0.0015 - mae: 0.0165 - val_loss: 0.0244 - val_mse: 0.0049 - val_mae: 0.0244
Epoch 87/400
0.0015 - mae: 0.0164 - val_loss: 0.0246 - val_mse: 0.0051 - val_mae: 0.0246
Epoch 88/400
0.0015 - mae: 0.0159 - val_loss: 0.0238 - val_mse: 0.0046 - val_mae: 0.0238
Epoch 89/400
0.0015 - mae: 0.0156 - val_loss: 0.0239 - val_mse: 0.0046 - val_mae: 0.0239
Epoch 90/400
```

```
0.0015 - mae: 0.0156 - val_loss: 0.0237 - val_mse: 0.0045 - val_mae: 0.0237
Epoch 91/400
0.0014 - mae: 0.0155 - val_loss: 0.0237 - val_mse: 0.0047 - val_mae: 0.0237
Epoch 92/400
0.0015 - mae: 0.0155 - val_loss: 0.0233 - val_mse: 0.0044 - val_mae: 0.0233
Epoch 93/400
0.0014 - mae: 0.0151 - val_loss: 0.0234 - val_mse: 0.0042 - val_mae: 0.0234
Epoch 94/400
0.0014 - mae: 0.0149 - val_loss: 0.0229 - val_mse: 0.0041 - val_mae: 0.0229
Epoch 95/400
0.0021 - mae: 0.0159 - val_loss: 0.0244 - val_mse: 0.0045 - val_mae: 0.0244
Epoch 96/400
0.0016 - mae: 0.0152 - val_loss: 0.0280 - val_mse: 0.0081 - val_mae: 0.0280
Epoch 97/400
0.0033 - mae: 0.0169 - val_loss: 0.0223 - val_mse: 0.0032 - val_mae: 0.0223
Epoch 98/400
0.0013 - mae: 0.0142 - val_loss: 0.0221 - val_mse: 0.0037 - val_mae: 0.0221
Epoch 99/400
0.0014 - mae: 0.0140 - val_loss: 0.0216 - val_mse: 0.0035 - val_mae: 0.0216
Epoch 100/400
0.0013 - mae: 0.0138 - val_loss: 0.0217 - val_mse: 0.0037 - val_mae: 0.0217
Epoch 101/400
0.0014 - mae: 0.0140 - val_loss: 0.0225 - val_mse: 0.0043 - val_mae: 0.0225
Epoch 102/400
0.0032 - mae: 0.0160 - val_loss: 0.0301 - val_mse: 0.0120 - val_mae: 0.0301
Epoch 103/400
0.0025 - mae: 0.0155 - val_loss: 0.0218 - val_mse: 0.0032 - val_mae: 0.0218
Epoch 104/400
0.0013 - mae: 0.0141 - val_loss: 0.0225 - val_mse: 0.0043 - val_mae: 0.0225
Epoch 105/400
0.0017 - mae: 0.0144 - val_loss: 0.0218 - val_mse: 0.0043 - val_mae: 0.0218
Epoch 106/400
```

```
0.0013 - mae: 0.0133 - val_loss: 0.0215 - val_mse: 0.0043 - val_mae: 0.0215
Epoch 107/400
0.0012 - mae: 0.0130 - val_loss: 0.0211 - val_mse: 0.0041 - val_mae: 0.0211
Epoch 108/400
0.0013 - mae: 0.0131 - val_loss: 0.0210 - val_mse: 0.0037 - val_mae: 0.0210
Epoch 109/400
0.0013 - mae: 0.0134 - val_loss: 0.0228 - val_mse: 0.0045 - val_mae: 0.0228
Epoch 110/400
0.0012 - mae: 0.0128 - val_loss: 0.0209 - val_mse: 0.0036 - val_mae: 0.0209
Epoch 111/400
0.0048 - mae: 0.0168 - val_loss: 0.0227 - val_mse: 0.0052 - val_mae: 0.0227
Epoch 112/400
0.0018 - mae: 0.0139 - val_loss: 0.0230 - val_mse: 0.0045 - val_mae: 0.0230
Epoch 113/400
0.0023 - mae: 0.0146 - val_loss: 0.0221 - val_mse: 0.0043 - val_mae: 0.0221
Epoch 114/400
0.0030 - mae: 0.0151 - val_loss: 0.0283 - val_mse: 0.0112 - val_mae: 0.0283
Epoch 115/400
0.0015 - mae: 0.0129 - val_loss: 0.0210 - val_mse: 0.0039 - val_mae: 0.0210
Epoch 116/400
0.0012 - mae: 0.0122 - val_loss: 0.0207 - val_mse: 0.0037 - val_mae: 0.0207
Epoch 117/400
0.0011 - mae: 0.0122 - val_loss: 0.0206 - val_mse: 0.0035 - val_mae: 0.0206
Epoch 118/400
0.0012 - mae: 0.0121 - val_loss: 0.0201 - val_mse: 0.0036 - val_mae: 0.0201
Epoch 119/400
0.0011 - mae: 0.0120 - val_loss: 0.0209 - val_mse: 0.0035 - val_mae: 0.0209
Epoch 120/400
0.0020 - mae: 0.0134 - val_loss: 0.0227 - val_mse: 0.0047 - val_mae: 0.0227
Epoch 121/400
0.0013 - mae: 0.0123 - val_loss: 0.0204 - val_mse: 0.0038 - val_mae: 0.0204
Epoch 122/400
```

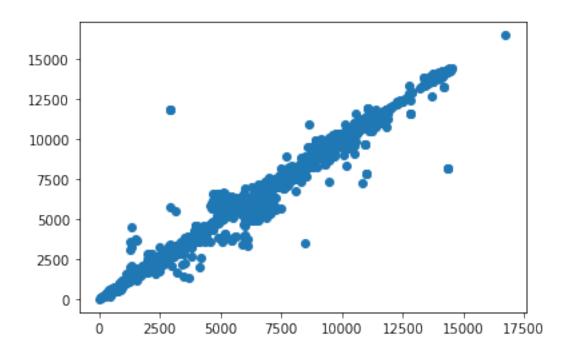
```
0.0011 - mae: 0.0118 - val_loss: 0.0209 - val_mse: 0.0039 - val_mae: 0.0209
Epoch 123/400
0.0011 - mae: 0.0119 - val_loss: 0.0256 - val_mse: 0.0086 - val_mae: 0.0256
Epoch 124/400
0.0063 - mae: 0.0166 - val_loss: 0.0201 - val_mse: 0.0035 - val_mae: 0.0201
Epoch 125/400
0.0017 - mae: 0.0128 - val_loss: 0.0232 - val_mse: 0.0063 - val_mae: 0.0232
Epoch 126/400
0.0015 - mae: 0.0127 - val_loss: 0.0210 - val_mse: 0.0036 - val_mae: 0.0210
Epoch 127/400
0.0011 - mae: 0.0116 - val_loss: 0.0203 - val_mse: 0.0037 - val_mae: 0.0203
Epoch 128/400
- mae: 0.0114
Epoch 00128: ReduceLROnPlateau reducing learning rate to 4.0000001899898055e-05.
0.0011 - mae: 0.0115 - val_loss: 0.0202 - val_mse: 0.0040 - val_mae: 0.0202
Epoch 129/400
0.0010 - mae: 0.0100 - val_loss: 0.0189 - val_mse: 0.0038 - val_mae: 0.0189
Epoch 130/400
9.8267e-04 - mae: 0.0095 - val_loss: 0.0188 - val_mse: 0.0038 - val_mae: 0.0188
Epoch 131/400
9.7636e-04 - mae: 0.0093 - val_loss: 0.0189 - val_mse: 0.0038 - val_mae: 0.0189
Epoch 132/400
9.8214e-04 - mae: 0.0092 - val loss: 0.0187 - val mse: 0.0038 - val mae: 0.0187
Epoch 133/400
9.7822e-04 - mae: 0.0091 - val_loss: 0.0186 - val_mse: 0.0038 - val_mae: 0.0186
Epoch 134/400
9.7715e-04 - mae: 0.0090 - val_loss: 0.0188 - val_mse: 0.0040 - val_mae: 0.0188
Epoch 135/400
9.7792e-04 - mae: 0.0090 - val loss: 0.0186 - val mse: 0.0039 - val mae: 0.0186
Epoch 136/400
9.7252e-04 - mae: 0.0090 - val_loss: 0.0188 - val_mse: 0.0040 - val_mae: 0.0188
Epoch 137/400
```

```
9.6900e-04 - mae: 0.0089 - val_loss: 0.0185 - val_mse: 0.0038 - val_mae: 0.0185
Epoch 138/400
9.6606e-04 - mae: 0.0089 - val_loss: 0.0186 - val_mse: 0.0039 - val_mae: 0.0186
Epoch 139/400
9.6645e-04 - mae: 0.0089 - val_loss: 0.0185 - val_mse: 0.0038 - val_mae: 0.0185
Epoch 140/400
9.6575e-04 - mae: 0.0088 - val loss: 0.0187 - val mse: 0.0040 - val mae: 0.0187
9.6213e-04 - mae: 0.0088 - val_loss: 0.0185 - val_mse: 0.0039 - val_mae: 0.0185
9.6247e-04 - mae: 0.0088 - val_loss: 0.0185 - val_mse: 0.0039 - val_mae: 0.0185
Epoch 143/400
9.5988e-04 - mae: 0.0088 - val_loss: 0.0186 - val_mse: 0.0041 - val_mae: 0.0186
9.5765e-04 - mae: 0.0087 - val_loss: 0.0185 - val_mse: 0.0039 - val_mae: 0.0185
Epoch 145/400
9.5199e-04 - mae: 0.0087 - val loss: 0.0185 - val mse: 0.0039 - val mae: 0.0185
Epoch 146/400
9.5085e-04 - mae: 0.0087 - val_loss: 0.0184 - val_mse: 0.0038 - val_mae: 0.0184
Epoch 147/400
9.4488e-04 - mae: 0.0087
Epoch 00147: ReduceLROnPlateau reducing learning rate to 8.000000525498762e-06.
9.4254e-04 - mae: 0.0087 - val loss: 0.0185 - val mse: 0.0039 - val mae: 0.0185
Epoch 148/400
9.3839e-04 - mae: 0.0084 - val_loss: 0.0182 - val_mse: 0.0038 - val_mae: 0.0182
Epoch 149/400
9.3657e-04 - mae: 0.0082 - val_loss: 0.0182 - val_mse: 0.0038 - val_mae: 0.0182
Epoch 150/400
9.3595e-04 - mae: 0.0082 - val_loss: 0.0182 - val_mse: 0.0038 - val_mae: 0.0182
Epoch 151/400
9.3385e-04 - mae: 0.0081 - val_loss: 0.0182 - val_mse: 0.0039 - val_mae: 0.0182
Epoch 152/400
```

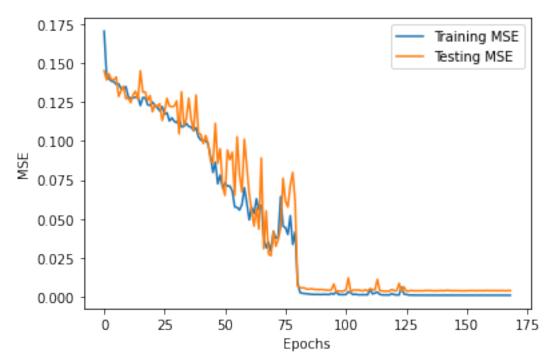
```
9.3459e-04 - mae: 0.0081 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 153/400
9.3390e-04 - mae: 0.0081 - val_loss: 0.0182 - val_mse: 0.0039 - val_mae: 0.0182
Epoch 154/400
9.3414e-04 - mae: 0.0081 - val_loss: 0.0182 - val_mse: 0.0039 - val_mae: 0.0182
Epoch 155/400
9.3394e-04 - mae: 0.0081 - val loss: 0.0181 - val mse: 0.0038 - val mae: 0.0181
Epoch 156/400
9.3356e-04 - mae: 0.0081 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 157/400
9.3133e-04 - mae: 0.0081 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 158/400
9.3253e-04 - mae: 0.0081 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
9.3164e-04 - mae: 0.0080 - val_loss: 0.0181 - val_mse: 0.0040 - val_mae: 0.0181
Epoch 160/400
9.3330e-04 - mae: 0.0080 - val loss: 0.0181 - val mse: 0.0039 - val mae: 0.0181
Epoch 161/400
9.3113e-04 - mae: 0.0080 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 162/400
9.3339e-04 - mae: 0.0080 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 163/400
9.3034e-04 - mae: 0.0080 - val loss: 0.0181 - val mse: 0.0039 - val mae: 0.0181
Epoch 164/400
9.3042e-04 - mae: 0.0080 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 165/400
9.3141e-04 - mae: 0.0080 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 166/400
9.3134e-04 - mae: 0.0080 - val_loss: 0.0181 - val_mse: 0.0039 - val_mae: 0.0181
Epoch 167/400
9.3240e-04 - mae: 0.0080 - val_loss: 0.0181 - val_mse: 0.0038 - val_mae: 0.0181
Epoch 168/400
```

3 Testing accuracy of Model with validation data

```
[139]: count
                5296.000000
      mean
                  -0.654780
       std
                  12.096885
       min
                -306.197923
       0.1%
                -155.362372
       1%
                 -27.918138
       5%
                  -7.758211
       25%
                  -0.691242
       50%
                  -0.015267
       75%
                   0.547683
       95%
                   7.036125
       99%
                  21.412407
       99.9%
                  46.142001
                  63.309345
      max
       Name: Percentage Error, dtype: float64
[140]: plt.scatter(compare['Expected'], compare['Result'])
       plt.show()
```



```
[141]: plt.plot(history.history['mse'],label='Training MSE')
   plt.plot(history.history['val_mse'],label='Testing MSE')
   plt.xlabel('Epochs')
   plt.ylabel('MSE')
   plt.legend()
   plt.show()
```



```
[145]: model.save('Trained_Models/Building_Model' + datetime.now().

strftime("%Y%m%d-%H%M%S") + '.h5')
```

4 Building Model Analysis

```
[146]: def clean_data(location, skiprows = 0):
           df_weather = pd.read_csv(location, skiprows=skiprows)
           df_weather = df_weather.drop(columns=['Hour', 'Minute'])
           df_weather = df_weather[df_weather.DNI != 0]
           #Take mean, max and min for each DNI in DataFrame and mean for everything
        \rightarrowelse
           max_dni = df_weather.groupby(['Year', 'Month', 'Day']).max().
        →reset_index()['DNI']
           min_dni = df_weather.groupby(['Year', 'Month', 'Day']).min().
        →reset_index()['DNI']
           df_weather = pd.DataFrame(df_weather.groupby(['Year', 'Month', 'Day']).
        →mean().reset_index())
           df_weather.insert(4, 'DNI Max', max_dni)
           df weather.insert(5, 'DNI Min', min dni)
           return df_weather
[147]: def training_prep(data, square_feet, building_type):
           data = data.loc[:, ['Year', 'Month', 'Day', 'DNI', 'DNI Max', 'DNI Min', |
        _{\hookrightarrow}'Wind Speed', 'Precipitable Water', 'Wind Direction', 'Relative Humidity', _{\sqcup}
        → 'Temperature', 'Pressure']]
           data.loc[:, 'Weekday'] = get_weekday2(data['Year'], data['Month'],__

→data['Day'])
           data = data.drop(['Year'], axis=1)
```

data.loc[:, 'Square Feet'] = square_feet
data.loc[:, 'Type'] = building_type

return data

```
[157]:
          Month Day
                             DNI DNI Max
                                                  Pressure Weekday
                                                                     Square Feet
                                                                                   Type
                                                993.888889
                                                                          100000
       0
              1
                   1
                       52.111111
                                      178
                                                                  0
                                                                                      1
       1
              1
                   2
                      396.000000
                                       751
                                               1011.400000
                                                                  0
                                                                          100000
                                                                                      1
       2
              1
                   3
                      299.700000
                                      752 ...
                                                997.400000
                                                                  0
                                                                          100000
                                                                                      1
                                                                  0
       3
                      281.900000
                                      576 ...
                                                997.300000
                                                                                      1
              1
                                                                          100000
       4
                   5
                       10.000000
                                        21 ...
                                                986.000000
                                                                  1
                                                                          100000
                                                                                      1
       [5 rows x 14 columns]
[158]: #Applying transform to data
       mi_test = x_scaler.transform(michigan_data)
[159]: #Testing model:
       mi_result = y_scaler.inverse_transform(model.predict(mi_test))
       compare = pd.DataFrame()
       compare['Month'] = michigan_data['Month']
       compare['Result'] = mi_result.reshape(1,-1)[0]
       compare.head()
[159]:
          Month
                      Result
                4895.604004
       1
              1 6315.085938
       2
              1 4469.236328
                 3986.015869
              1 4031.808105
[160]: compare = pd.DataFrame(compare.groupby(['Month']).sum().reset_index())
       actual = [212259, 240083, 218423, 233777, 240106, 272017, 300123, 295701, ____
       →288447, 254802, 228097, 220258]
       compare['Actual'] = actual
       compare['Difference'] = compare['Actual'] - compare['Result']
       compare['Percentage Error'] = 100 * compare['Difference']/compare['Actual']
       compare.head(12)
[160]:
           Month
                         Result Actual
                                             Difference Percentage Error
       0
                  134455.828125
                                 212259
                                           77803.171875
                                                                36.654828
       1
               2 143473.031250 240083
                                           96609.968750
                                                                40.240237
       2
                  194498.750000 218423
                                           23924.250000
                                                                10.953173
       3
               4
                  204883.156250 233777
                                           28893.843750
                                                                12.359575
                                           45884.546875
       4
                  194221.453125 240106
               5
                                                                19.110121
                  180275.687500 272017
       5
               6
                                           91741.312500
                                                                33.726316
       6
               7
                  178017.578125 300123 122105.421875
                                                                40.685126
       7
               8
                  177075.234375 295701
                                         118625.765625
                                                                40.116796
                 190250.078125 288447
       8
               9
                                           98196.921875
                                                                34.043315
       9
              10 201368.203125 254802
                                           53433.796875
                                                                20.970713
       10
              11 175134.781250 228097
                                           52962.218750
                                                                23.219165
       11
              12 154103.718750 220258
                                           66154.281250
                                                                30.034905
```

```
[161]: compare.describe()
[161]:
                                Result
                 Month
                                               Actual
                                                          Difference Percentage Error
              12.000000
                             12.000000
                                            12.000000
                                                           12.000000
                                                                             12.000000
      count
      mean
              6.500000
                        177313.125000
                                        250341.083333
                                                        73027.958333
                                                                             28.509523
                          22607.332031
                                                        33001.252345
      std
               3.605551
                                         31378.512646
                                                                             10.826360
      min
              1.000000
                        134455.828125
                                        212259.000000
                                                        23924.250000
                                                                             10.953173
      25%
              3.750000
                        169877.015625
                                        226137.250000
                                                        51192.800781
                                                                             20.505565
      50%
              6.500000
                        179146.632812
                                       240094.500000
                                                        71978.726562
                                                                             31.880610
      75%
              9.250000
                        194290.777344
                                        276124.500000
                                                        97006.707031
                                                                             37.520320
              12.000000
                        204883.156250
                                       300123.000000 122105.421875
                                                                             40.685126
      max
          Comparison against UIUC data
[153]: |uiuc_test = pd.read_csv('https://raw.githubusercontent.com/A-Wadhwani/
       →ME597-Project/main/Datasets/UIUC PowerWeatherData.csv')
       #Adding other relevant data, including square feet and type
      uiuc test['Square Feet'] = 100000
       #Laboratory
      uiuc test['Type'] = 1
      uiuc_actual = uiuc_test['Power Consumption']
      uiuc_test = uiuc_test.drop(['Building Name', 'University Name', 'Year', 'Power_
       uiuc test.head()
[153]:
                                                                   Square Feet
         Month Day
                       DNI Mean
                                 DNI Max ...
                                                Pressure
                                                          Weekday
      0
             10
                      597.916667
                                      898
                                              988.333333
                                                                        100000
      1
             10
                     332.250000
                                      772 ... 986.250000
                                                                0
                                                                        100000
      2
             10
                   3
                     408.000000
                                      923 ...
                                              991.555556
                                                                0
                                                                        100000
                                                                                   1
      3
                     617.250000
                                              999.416667
                                                                0
             10
                                      931 ...
                                                                        100000
                                                                                   1
                                      810 ...
             10
                      309.400000
                                              990.500000
                                                                1
                                                                        100000
                                                                                   1
      [5 rows x 14 columns]
[154]: #Applying transform to data
      uiuc_test = x_scaler.transform(uiuc_test)
[155]: #Testing model:
      uiuc result = y scaler.inverse transform(model.predict(uiuc test))
      compare = pd.DataFrame()
      compare['Actual'] = uiuc_actual
      compare['Result'] = uiuc_result.reshape(1,-1)[0]
      compare['Difference'] = compare['Actual'] - compare['Result']
      compare['Percentage Error'] = 100 * compare['Difference']/compare['Actual']
```

compare.describe()

```
[155]:
                   Actual
                                 Result
                                          Difference
                                                      Percentage Error
                                                              51.000000
                51.000000
                              51.000000
                                           51.000000
       count
      mean
              6189.156863
                           6120.660156
                                           68.496223
                                                               0.870158
       std
               228.978372
                           1833.974487
                                         1866.649114
                                                              30.106029
              5069.000000
                            975.114746 -2872.380859
                                                             -46.009625
      min
       25%
              6142.000000
                           5669.620117 -1163.810547
                                                             -18.707773
       50%
              6243.000000
                           6721.865723
                                         -519.716797
                                                              -7.973562
       75%
              6301.000000
                           7376.884521
                                          449.379883
                                                               7.327076
                           9115.380859
              6518.000000
       max
                                         5351.885254
                                                              84.588039
```

[156]: plt.hist(compare['Percentage Error']) plt.show()

