DL Lab Exp No.1

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

[2]:
```python
df = pd.read_csv("D:/BE Lab Practicals/Sem 8/DL/Lab 1/1_boston_housing.csv")
X = df.loc[:, df.columns != 'MEDV']
y = df.loc[:, df.columns == 'MEDV']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=123)
df
```

[2]:
```
        crim    zn  indus  chas    nox     rm   age     dis  rad  tax  \
0    0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296
1    0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242
2    0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242
3    0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222
4    0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222
..       …     …      …     …      …      …     …       …   …    …
501  0.06263   0.0  11.93     0  0.573  6.593  69.1  2.4786    1  273
502  0.04527   0.0  11.93     0  0.573  6.120  76.7  2.2875    1  273
503  0.06076   0.0  11.93     0  0.573  6.976  91.0  2.1675    1  273
504  0.10959   0.0  11.93     0  0.573  6.794  89.3  2.3889    1  273
505  0.04741   0.0  11.93     0  0.573  6.030  80.8  2.5050    1  273

     ptratio       b  lstat  MEDV
0       15.3  396.90   4.98  24.0
1       17.8  396.90   9.14  21.6
2       17.8  392.83   4.03  34.7
3       18.7  394.63   2.94  33.4
4       18.7  396.90   5.33  36.2
..       …       …      …     …
```

```
501      21.0  391.99   9.67  22.4
502      21.0  396.90   9.08  20.6
503      21.0  396.90   5.64  23.9
504      21.0  393.45   6.48  22.0
505      21.0  396.90   7.88  11.9

[506 rows x 14 columns]
```

[3]:
```
mms = MinMaxScaler()
mms.fit(X_train)
X_train = mms.transform(X_train)
X_test = mms.transform(X_test)
```

[4]:
```
model = Sequential()
model.add(Dense(128, input_shape=(13, ), activation='relu', name='dense_1'))
model.add(Dense(64, activation='relu', name='dense_2'))
model.add(Dense(1, activation='linear', name='dense_output'))
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
model.summary()
```

```
C:\Users\athar\AppData\Local\Programs\Python\Python311\Lib\site-
packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Model: "sequential"


 Layer (type)                         Output Shape                          ␣
↪Param #

 dense_1 (Dense)                      (None, 128)                             ␣
↪1,792

 dense_2 (Dense)                      (None, 64)                              ␣
↪8,256

 dense_output (Dense)                 (None, 1)                                 ␣
↪ 65


 Total params: 10,113 (39.50 KB)


 Trainable params: 10,113 (39.50 KB)
```

Non-trainable params: 0 (0.00 B)

[5]:
```
history = model.fit(X_train, y_train, epochs=100, validation_split=0.05,
 ↪verbose = 1)
```

```
Epoch 1/100
11/11               2s 31ms/step -
loss: 599.3525 - mae: 22.6281 - val_loss: 592.7638 - val_mae: 22.3914
Epoch 2/100
11/11               0s 12ms/step -
loss: 519.9579 - mae: 20.7516 - val_loss: 530.1406 - val_mae: 20.9214
Epoch 3/100
11/11               0s 10ms/step -
loss: 453.7683 - mae: 19.2084 - val_loss: 434.6219 - val_mae: 18.4141
Epoch 4/100
11/11               0s 10ms/step -
loss: 381.7032 - mae: 17.1277 - val_loss: 307.0502 - val_mae: 14.4973
Epoch 5/100
11/11               0s 9ms/step - loss:
243.1997 - mae: 12.5403 - val_loss: 185.7538 - val_mae: 10.0677
Epoch 6/100
11/11               0s 9ms/step - loss:
162.7295 - mae: 10.1097 - val_loss: 129.7730 - val_mae: 8.1589
Epoch 7/100
11/11               0s 18ms/step -
loss: 137.8909 - mae: 9.0341 - val_loss: 116.0482 - val_mae: 7.8229
Epoch 8/100
11/11               0s 20ms/step -
loss: 108.4955 - mae: 7.9685 - val_loss: 108.2117 - val_mae: 7.3912
Epoch 9/100
11/11               0s 16ms/step -
loss: 106.2049 - mae: 7.7470 - val_loss: 98.9827 - val_mae: 6.9410
Epoch 10/100
11/11               0s 17ms/step -
loss: 81.5944 - mae: 6.5527 - val_loss: 88.3723 - val_mae: 6.5452
Epoch 11/100
11/11               0s 16ms/step -
loss: 81.1228 - mae: 6.6380 - val_loss: 79.8962 - val_mae: 6.2418
Epoch 12/100
11/11               0s 18ms/step -
loss: 68.0075 - mae: 5.8913 - val_loss: 75.5469 - val_mae: 5.8762
Epoch 13/100
11/11               0s 8ms/step - loss:
65.3576 - mae: 5.5475 - val_loss: 71.0457 - val_mae: 5.7781
Epoch 14/100
11/11               0s 8ms/step - loss:
44.7903 - mae: 4.7093 - val_loss: 67.3035 - val_mae: 5.8614
```

```
Epoch 15/100
11/11            0s 8ms/step - loss:
45.5874 - mae: 4.8079 - val_loss: 65.7170 - val_mae: 5.6781
Epoch 16/100
11/11            0s 19ms/step -
loss: 49.5205 - mae: 4.9284 - val_loss: 63.7373 - val_mae: 5.5918
Epoch 17/100
11/11            0s 17ms/step -
loss: 50.6014 - mae: 4.9113 - val_loss: 61.6457 - val_mae: 5.5610
Epoch 18/100
11/11            0s 15ms/step -
loss: 39.0823 - mae: 4.5099 - val_loss: 59.8784 - val_mae: 5.4958
Epoch 19/100
11/11            0s 14ms/step -
loss: 41.8102 - mae: 4.4395 - val_loss: 58.1691 - val_mae: 5.4223
Epoch 20/100
11/11            0s 20ms/step -
loss: 50.5238 - mae: 4.8046 - val_loss: 57.5194 - val_mae: 5.1853
Epoch 21/100
11/11            0s 32ms/step -
loss: 38.2364 - mae: 4.2098 - val_loss: 54.8504 - val_mae: 5.2273
Epoch 22/100
11/11            0s 9ms/step - loss:
33.1024 - mae: 4.0690 - val_loss: 52.9484 - val_mae: 5.1660
Epoch 23/100
11/11            0s 16ms/step -
loss: 26.1383 - mae: 3.6345 - val_loss: 51.7592 - val_mae: 5.0160
Epoch 24/100
11/11            0s 9ms/step - loss:
28.0990 - mae: 3.7513 - val_loss: 49.5380 - val_mae: 4.9749
Epoch 25/100
11/11            0s 9ms/step - loss:
31.1979 - mae: 3.9553 - val_loss: 47.8735 - val_mae: 4.8658
Epoch 26/100
11/11            0s 9ms/step - loss:
39.4065 - mae: 4.1987 - val_loss: 46.6029 - val_mae: 4.7804
Epoch 27/100
11/11            0s 9ms/step - loss:
30.0178 - mae: 3.7873 - val_loss: 45.5111 - val_mae: 4.7328
Epoch 28/100
11/11            0s 9ms/step - loss:
27.5667 - mae: 3.5036 - val_loss: 44.1736 - val_mae: 4.6975
Epoch 29/100
11/11            0s 12ms/step -
loss: 28.6459 - mae: 3.4918 - val_loss: 42.0032 - val_mae: 4.6673
Epoch 30/100
11/11            0s 22ms/step -
loss: 19.8351 - mae: 3.1303 - val_loss: 42.4621 - val_mae: 4.5927
```

```
Epoch 31/100
11/11            0s 18ms/step -
loss: 30.3126 - mae: 3.5961 - val_loss: 40.3847 - val_mae: 4.5605
Epoch 32/100
11/11            0s 15ms/step -
loss: 25.2790 - mae: 3.4840 - val_loss: 39.8099 - val_mae: 4.5066
Epoch 33/100
11/11            0s 10ms/step -
loss: 25.4624 - mae: 3.3885 - val_loss: 39.7459 - val_mae: 4.4625
Epoch 34/100
11/11            0s 23ms/step -
loss: 20.4141 - mae: 3.0293 - val_loss: 37.6769 - val_mae: 4.4186
Epoch 35/100
11/11            0s 26ms/step -
loss: 22.0317 - mae: 3.0758 - val_loss: 36.9575 - val_mae: 4.3696
Epoch 36/100
11/11            0s 19ms/step -
loss: 17.0361 - mae: 2.9434 - val_loss: 36.8875 - val_mae: 4.2948
Epoch 37/100
11/11            0s 18ms/step -
loss: 16.9460 - mae: 2.9350 - val_loss: 36.0707 - val_mae: 4.2415
Epoch 38/100
11/11            0s 21ms/step -
loss: 17.5669 - mae: 2.9728 - val_loss: 35.6371 - val_mae: 4.1866
Epoch 39/100
11/11            0s 18ms/step -
loss: 17.4077 - mae: 2.8045 - val_loss: 35.3211 - val_mae: 4.1318
Epoch 40/100
11/11            0s 24ms/step -
loss: 22.2370 - mae: 3.1505 - val_loss: 35.3869 - val_mae: 4.0734
Epoch 41/100
11/11            0s 22ms/step -
loss: 16.5623 - mae: 2.8740 - val_loss: 33.9567 - val_mae: 4.0309
Epoch 42/100
11/11            0s 23ms/step -
loss: 16.7403 - mae: 2.9087 - val_loss: 33.5914 - val_mae: 3.9662
Epoch 43/100
11/11            0s 18ms/step -
loss: 16.6586 - mae: 2.7992 - val_loss: 33.6023 - val_mae: 3.9275
Epoch 44/100
11/11            0s 14ms/step -
loss: 13.8735 - mae: 2.5669 - val_loss: 33.1885 - val_mae: 3.8750
Epoch 45/100
11/11            0s 9ms/step - loss:
19.8690 - mae: 2.8959 - val_loss: 32.1225 - val_mae: 3.8298
Epoch 46/100
11/11            0s 9ms/step - loss:
13.4032 - mae: 2.6537 - val_loss: 33.3223 - val_mae: 3.8139
```

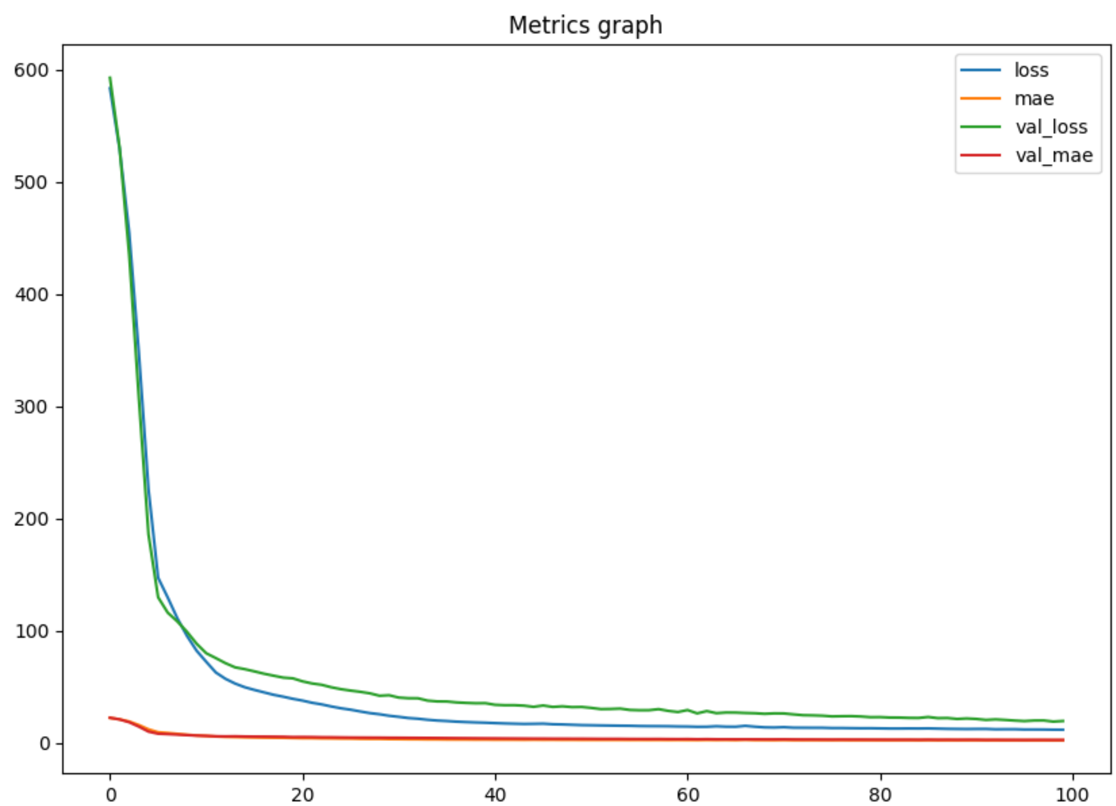
```
Epoch 47/100
11/11            0s 19ms/step -
loss: 19.4675 - mae: 3.0259 - val_loss: 32.0413 - val_mae: 3.7554
Epoch 48/100
11/11            0s 16ms/step -
loss: 16.5615 - mae: 2.7042 - val_loss: 32.5751 - val_mae: 3.7518
Epoch 49/100
11/11            0s 13ms/step -
loss: 15.6666 - mae: 2.7556 - val_loss: 31.8818 - val_mae: 3.7130
Epoch 50/100
11/11            0s 19ms/step -
loss: 19.4993 - mae: 2.8207 - val_loss: 32.0210 - val_mae: 3.7076
Epoch 51/100
11/11            0s 20ms/step -
loss: 16.3463 - mae: 2.8116 - val_loss: 31.1816 - val_mae: 3.6473
Epoch 52/100
11/11            0s 18ms/step -
loss: 18.1211 - mae: 2.8145 - val_loss: 30.1189 - val_mae: 3.5876
Epoch 53/100
11/11            0s 18ms/step -
loss: 19.2574 - mae: 2.8843 - val_loss: 30.2295 - val_mae: 3.5801
Epoch 54/100
11/11            0s 16ms/step -
loss: 15.9205 - mae: 2.6128 - val_loss: 30.5666 - val_mae: 3.5671
Epoch 55/100
11/11            0s 11ms/step -
loss: 13.4778 - mae: 2.4481 - val_loss: 29.3664 - val_mae: 3.4977
Epoch 56/100
11/11            0s 12ms/step -
loss: 13.0093 - mae: 2.5294 - val_loss: 29.0954 - val_mae: 3.4742
Epoch 57/100
11/11            0s 11ms/step -
loss: 14.9983 - mae: 2.6087 - val_loss: 29.1261 - val_mae: 3.4568
Epoch 58/100
11/11            0s 11ms/step -
loss: 19.8223 - mae: 2.8426 - val_loss: 30.0584 - val_mae: 3.4738
Epoch 59/100
11/11            0s 9ms/step - loss:
14.9067 - mae: 2.6054 - val_loss: 28.5109 - val_mae: 3.3949
Epoch 60/100
11/11            0s 9ms/step - loss:
16.4412 - mae: 2.7286 - val_loss: 27.5355 - val_mae: 3.3555
Epoch 61/100
11/11            0s 22ms/step -
loss: 14.0985 - mae: 2.4072 - val_loss: 29.2501 - val_mae: 3.4035
Epoch 62/100
11/11            0s 16ms/step -
loss: 12.1183 - mae: 2.4811 - val_loss: 26.3162 - val_mae: 3.2600
```

```
Epoch 63/100
11/11            0s 14ms/step -
loss: 15.0962 - mae: 2.7069 - val_loss: 28.3382 - val_mae: 3.3436
Epoch 64/100
11/11            0s 10ms/step -
loss: 13.8295 - mae: 2.6908 - val_loss: 26.4929 - val_mae: 3.2302
Epoch 65/100
11/11            0s 10ms/step -
loss: 14.4137 - mae: 2.5850 - val_loss: 27.0759 - val_mae: 3.2298
Epoch 66/100
11/11            0s 9ms/step - loss:
11.0371 - mae: 2.3867 - val_loss: 27.0140 - val_mae: 3.2018
Epoch 67/100
11/11            0s 11ms/step -
loss: 17.5901 - mae: 2.8000 - val_loss: 26.6583 - val_mae: 3.2007
Epoch 68/100
11/11            0s 9ms/step - loss:
16.2860 - mae: 2.7283 - val_loss: 26.4216 - val_mae: 3.1852
Epoch 69/100
11/11            0s 9ms/step - loss:
14.5334 - mae: 2.5732 - val_loss: 25.9116 - val_mae: 3.1429
Epoch 70/100
11/11            0s 10ms/step -
loss: 11.1943 - mae: 2.3397 - val_loss: 26.2909 - val_mae: 3.1485
Epoch 71/100
11/11            0s 8ms/step - loss:
17.5472 - mae: 2.6497 - val_loss: 26.2369 - val_mae: 3.1763
Epoch 72/100
11/11            0s 10ms/step -
loss: 17.3370 - mae: 2.5819 - val_loss: 25.4039 - val_mae: 3.0914
Epoch 73/100
11/11            0s 10ms/step -
loss: 10.0929 - mae: 2.2251 - val_loss: 24.6764 - val_mae: 3.0337
Epoch 74/100
11/11            0s 9ms/step - loss:
15.2639 - mae: 2.5918 - val_loss: 24.5327 - val_mae: 3.0215
Epoch 75/100
11/11            0s 10ms/step -
loss: 13.5801 - mae: 2.5440 - val_loss: 24.2452 - val_mae: 2.9845
Epoch 76/100
11/11            0s 10ms/step -
loss: 10.3105 - mae: 2.3366 - val_loss: 23.6327 - val_mae: 2.9428
Epoch 77/100
11/11            0s 10ms/step -
loss: 14.9142 - mae: 2.6261 - val_loss: 23.7800 - val_mae: 2.9584
Epoch 78/100
11/11            0s 17ms/step -
loss: 12.4432 - mae: 2.4908 - val_loss: 23.8568 - val_mae: 2.9416
```

```
Epoch 79/100
11/11            0s 10ms/step -
loss: 12.5490 - mae: 2.4084 - val_loss: 23.5368 - val_mae: 2.9310
Epoch 80/100
11/11            0s 8ms/step - loss:
13.2866 - mae: 2.4947 - val_loss: 22.9148 - val_mae: 2.8860
Epoch 81/100
11/11            0s 9ms/step - loss:
11.5557 - mae: 2.3989 - val_loss: 22.9837 - val_mae: 2.8866
Epoch 82/100
11/11            0s 9ms/step - loss:
10.1977 - mae: 2.3017 - val_loss: 22.5897 - val_mae: 2.8527
Epoch 83/100
11/11            0s 9ms/step - loss:
12.5821 - mae: 2.5397 - val_loss: 22.5403 - val_mae: 2.8519
Epoch 84/100
11/11            0s 10ms/step -
loss: 19.7206 - mae: 2.7802 - val_loss: 22.2724 - val_mae: 2.8432
Epoch 85/100
11/11            0s 22ms/step -
loss: 12.3541 - mae: 2.3539 - val_loss: 22.2063 - val_mae: 2.8074
Epoch 86/100
11/11            0s 11ms/step -
loss: 14.6840 - mae: 2.5424 - val_loss: 23.0716 - val_mae: 2.8628
Epoch 87/100
11/11            0s 9ms/step - loss:
14.8926 - mae: 2.5293 - val_loss: 22.0407 - val_mae: 2.8011
Epoch 88/100
11/11            0s 8ms/step - loss:
13.9023 - mae: 2.4381 - val_loss: 22.1589 - val_mae: 2.8323
Epoch 89/100
11/11            0s 8ms/step - loss:
11.6399 - mae: 2.3888 - val_loss: 21.3343 - val_mae: 2.7712
Epoch 90/100
11/11            0s 22ms/step -
loss: 12.4772 - mae: 2.3343 - val_loss: 21.7568 - val_mae: 2.8121
Epoch 91/100
11/11            0s 10ms/step -
loss: 14.7667 - mae: 2.4099 - val_loss: 21.3363 - val_mae: 2.7876
Epoch 92/100
11/11            0s 12ms/step -
loss: 11.9230 - mae: 2.2700 - val_loss: 20.4876 - val_mae: 2.7051
Epoch 93/100
11/11            0s 11ms/step -
loss: 10.8603 - mae: 2.3354 - val_loss: 20.9458 - val_mae: 2.7177
Epoch 94/100
11/11            0s 14ms/step -
loss: 10.9182 - mae: 2.3706 - val_loss: 20.4693 - val_mae: 2.6882
```

```
Epoch 95/100
11/11              0s 12ms/step -
loss: 9.5058 - mae: 2.2632 - val_loss: 19.9006 - val_mae: 2.6559
Epoch 96/100
11/11              0s 12ms/step -
loss: 10.6962 - mae: 2.2840 - val_loss: 19.4364 - val_mae: 2.6370
Epoch 97/100
11/11              0s 12ms/step -
loss: 13.4888 - mae: 2.4289 - val_loss: 19.9406 - val_mae: 2.6649
Epoch 98/100
11/11              0s 13ms/step -
loss: 12.5843 - mae: 2.3256 - val_loss: 19.9902 - val_mae: 2.6778
Epoch 99/100
11/11              0s 11ms/step -
loss: 13.5059 - mae: 2.4637 - val_loss: 18.9751 - val_mae: 2.6314
Epoch 100/100
11/11              0s 19ms/step -
loss: 9.9654 - mae: 2.2208 - val_loss: 19.4992 - val_mae: 2.6429
```

[6]:
```
pd.DataFrame(history.history).plot(figsize=(10,7))
plt.title("Metrics graph")
plt.show()
```

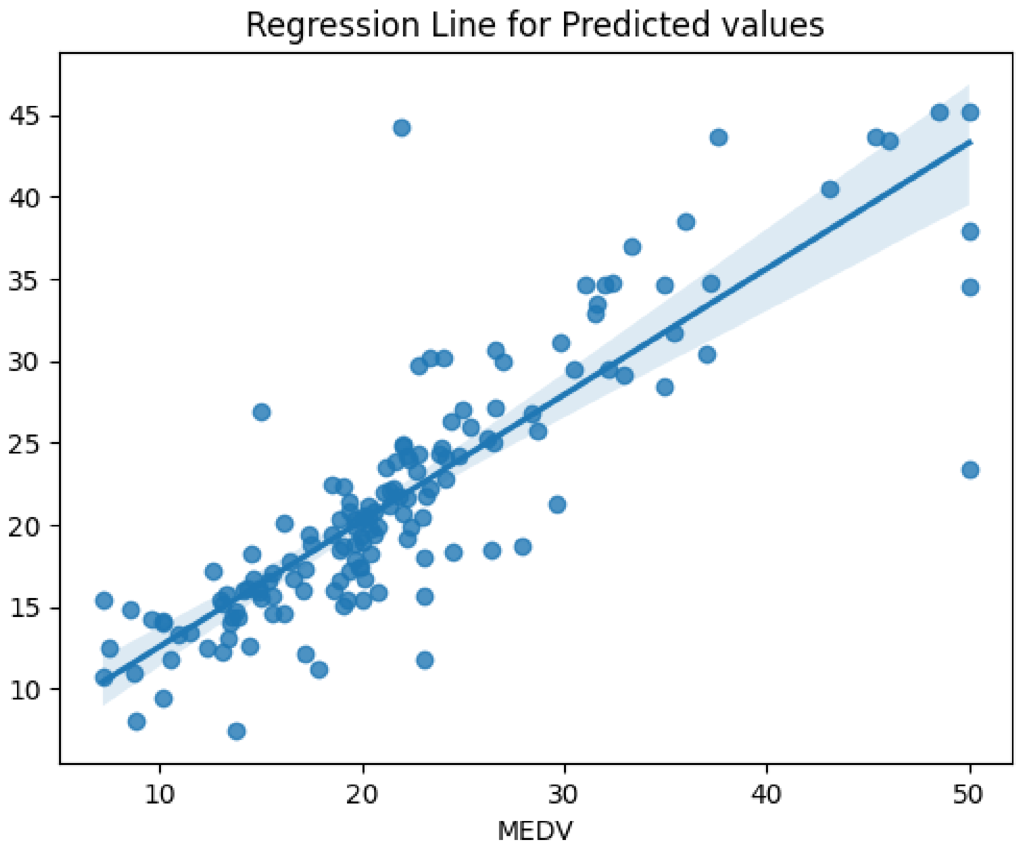


[7]:
```python
mse_nn, mae_nn = model.evaluate(X_test, y_test)
print('Mean squared error on test data: ', mse_nn)
print('Mean absolute error on test data: ', mae_nn)

rmse_nn = np.sqrt(mse_nn)
print('Root Mean Squared Error on test data: ', rmse_nn)

r2_nn = r2_score(y_test, model.predict(X_test))
print('R-squared on test data: ', r2_nn)
```

```
5/5              0s 10ms/step - loss:
30.0181 - mae: 3.3088
Mean squared error on test data:  21.736732482910156
Mean absolute error on test data:  2.973034620285034
Root Mean Squared Error on test data:  4.662266882419984
5/5              0s 18ms/step
R-squared on test data:  0.7310745716094971
```

[8]:
```python
sns.regplot(x=y_test, y=model.predict(X_test))
plt.title("Regression Line for Predicted values")
plt.show()
```

```
5/5              0s 11ms/step
```


Regression Line for Predicted values
45
40
35
30
25
20
15
10
10
20
30
40
50
MEDV