

PRACTICAL 1

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
from google.colab import files
uploaded = files.upload()

df = pd.read_csv(list(uploaded.keys())[0])
print(df.head())

X = df.iloc[:, :-1].values # All columns except last one as features
y = df.iloc[:, -1].values # Last column as target (house price)

scaler = StandardScaler()
X = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    layers.Dense(32, activation='relu'),
    layers.Dense(16, activation='relu'),
    layers.Dense(1) # Output layer for regression
])
```

```
model.compile(optimizer='adam', loss='mse', metrics=['mae'])
```

```
# Train the model
```

```
history = model.fit(X_train, y_train, epochs=100, validation_data=(X_test, y_test),  
batch_size=32, verbose=1)
```

```
# Evaluate the model
```

```
test_loss, test_mae = model.evaluate(X_test, y_test, verbose=1)
```

```
print(f"\nTest MAE: {test_mae:.2f}")
```

```
# Predict on test set
```

```
y_pred = model.predict(X_test)
```

```
# Scatter plot of actual vs predicted prices
```

```
plt.figure(figsize=(8, 6))
```

```
plt.scatter(y_test, y_pred, alpha=0.7)
```

```
plt.xlabel("Actual Prices")
```

```
plt.ylabel("Predicted Prices")
```

```
plt.title("Actual vs Predicted Prices (Boston Housing)")
```

```
plt.grid(True)
```

```
plt.show()
```

```
# Plot training history (MAE over epochs)
```

```
plt.figure(figsize=(8, 6))
```

```
plt.plot(history.history['mae'], label='Train MAE')
```

```
plt.plot(history.history['val_mae'], label='Validation MAE')
```

```
plt.xlabel("Epochs")
```

```
plt.ylabel("Mean Absolute Error")
```

```
plt.legend()
plt.title("Training History")
plt.grid(True)
plt.show()
```

OUTPUT:

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving BostonHousing.csv to BostonHousing.csv

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	\
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	

	b	lstat	medv
0	396.90	4.98	24.0
1	396.90	9.14	21.6
2	392.83	4.03	34.7
3	394.63	2.94	33.4
4	396.90	5.33	36.2

Epoch 1/100

/usr/local/lib/python3.11/dist-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)
```

13/13 ————— **2s** 27ms/step - loss: 571.4792 - mae: 22.0476 - val_loss: 471.1597 - val_mae: 19.9952

Epoch 2/100

13/13 ————— **0s** 8ms/step - loss: 529.7705 - mae: 20.9969 - val_loss: 403.0136 - val_mae: 18.2745

Epoch 3/100

13/13 ————— **0s** 8ms/step - loss: 477.5102 - mae: 19.7289 - val_loss: 299.9744 - val_mae: 15.4551

Epoch 4/100

13/13 ————— **0s** 8ms/step - loss: 304.8325 - mae: 15.3659 - val_loss: 168.2961 - val_mae: 11.0135

Epoch 5/100

13/13 ————— **0s** 11ms/step - loss: 181.0786 - mae: 11.0079 - val_loss: 67.8324 - val_mae: 6.3521

Epoch 6/100

13/13 ————— **0s** 8ms/step - loss: 86.9599 - mae: 7.1571 - val_loss: 46.2475 - val_mae: 5.0032

Epoch 7/100

13/13 ————— **0s** 8ms/step - loss: 54.3959 - mae: 5.9055 - val_loss: 35.2659 - val_mae: 4.3086

Epoch 8/100

13/13 ————— **0s** 11ms/step - loss: 36.1553 - mae: 4.6831 - val_loss: 31.4181 - val_mae: 3.8609

Epoch 9/100

13/13 ————— **0s** 8ms/step - loss: 31.0510 - mae: 4.1397 - val_loss: 27.8584 - val_mae: 3.5411

Epoch 10/100

13/13 ————— **0s** 8ms/step - loss: 25.6515 - mae: 3.6241 - val_loss: 25.7116 - val_mae: 3.3729

Epoch 11/100

13/13 ————— **0s** 8ms/step - loss: 23.2559 - mae: 3.5709 - val_loss: 24.1313 - val_mae: 3.2088

Epoch 12/100

13/13 ————— **0s** 8ms/step - loss: 23.4509 - mae:
3.6264 - val_loss: 22.6413 - val_mae: 3.1172

Epoch 13/100

13/13 ————— **0s** 8ms/step - loss: 23.3846 - mae:
3.4492 - val_loss: 21.6731 - val_mae: 3.0039

Epoch 14/100

13/13 ————— **0s** 9ms/step - loss: 18.6011 - mae:
3.1556 - val_loss: 20.6647 - val_mae: 2.9117

Epoch 15/100

13/13 ————— **0s** 12ms/step - loss: 18.0669 - mae:
3.1767 - val_loss: 19.7427 - val_mae: 2.8504

Epoch 16/100

13/13 ————— **0s** 9ms/step - loss: 17.0902 - mae:
3.0953 - val_loss: 19.1086 - val_mae: 2.8181

Epoch 17/100

13/13 ————— **0s** 8ms/step - loss: 21.5475 - mae:
3.2757 - val_loss: 18.3867 - val_mae: 2.7472

Epoch 18/100

13/13 ————— **0s** 11ms/step - loss: 14.7240 - mae:
2.9130 - val_loss: 18.1541 - val_mae: 2.6809

Epoch 19/100

13/13 ————— **0s** 8ms/step - loss: 16.6628 - mae:
2.9423 - val_loss: 17.4214 - val_mae: 2.6483

Epoch 20/100

13/13 ————— **0s** 9ms/step - loss: 17.3435 - mae:
2.9449 - val_loss: 17.0360 - val_mae: 2.6473

Epoch 21/100

13/13 ————— **0s** 9ms/step - loss: 15.9060 - mae:
2.7930 - val_loss: 16.3563 - val_mae: 2.6206

Epoch 22/100

13/13 ————— **0s** 9ms/step - loss: 16.1693 - mae: 2.8429 - val_loss: 15.9937 - val_mae: 2.5851

Epoch 23/100

13/13 ————— **0s** 8ms/step - loss: 12.4540 - mae: 2.5759 - val_loss: 15.9420 - val_mae: 2.5942

Epoch 24/100

13/13 ————— **0s** 8ms/step - loss: 15.1260 - mae: 2.6627 - val_loss: 15.4236 - val_mae: 2.5608

Epoch 25/100

13/13 ————— **0s** 8ms/step - loss: 13.0098 - mae: 2.5518 - val_loss: 15.0017 - val_mae: 2.5334

Epoch 26/100

13/13 ————— **0s** 9ms/step - loss: 15.1213 - mae: 2.6450 - val_loss: 14.7071 - val_mae: 2.5083

Epoch 27/100

13/13 ————— **0s** 9ms/step - loss: 13.3143 - mae: 2.6151 - val_loss: 14.4316 - val_mae: 2.5172

Epoch 28/100

13/13 ————— **0s** 8ms/step - loss: 14.5751 - mae: 2.6317 - val_loss: 14.4699 - val_mae: 2.4936

Epoch 29/100

13/13 ————— **0s** 8ms/step - loss: 11.6692 - mae: 2.4788 - val_loss: 13.9572 - val_mae: 2.4952

Epoch 30/100

13/13 ————— **0s** 8ms/step - loss: 11.9264 - mae: 2.4706 - val_loss: 13.8207 - val_mae: 2.4698

Epoch 31/100

13/13 ————— **0s** 8ms/step - loss: 12.2496 - mae: 2.5322 - val_loss: 13.5760 - val_mae: 2.4559

Epoch 32/100

13/13 ————— **0s** 8ms/step - loss: 12.4958 - mae: 2.5310 - val_loss: 13.4944 - val_mae: 2.4967

Epoch 33/100

13/13 ————— **0s** 9ms/step - loss: 10.8622 - mae: 2.4198 - val_loss: 13.4468 - val_mae: 2.4407

Epoch 34/100

13/13 ————— **0s** 8ms/step - loss: 10.7568 - mae: 2.3555 - val_loss: 13.1576 - val_mae: 2.4266

Epoch 35/100

13/13 ————— **0s** 8ms/step - loss: 11.7021 - mae: 2.4592 - val_loss: 13.1434 - val_mae: 2.4612

Epoch 36/100

13/13 ————— **0s** 8ms/step - loss: 12.1847 - mae: 2.4193 - val_loss: 12.9056 - val_mae: 2.4020

Epoch 37/100

13/13 ————— **0s** 8ms/step - loss: 11.3211 - mae: 2.3619 - val_loss: 12.9186 - val_mae: 2.4515

Epoch 38/100

13/13 ————— **0s** 9ms/step - loss: 9.8416 - mae: 2.2986 - val_loss: 12.7198 - val_mae: 2.4119

Epoch 39/100

13/13 ————— **0s** 11ms/step - loss: 11.2098 - mae: 2.4144 - val_loss: 12.6719 - val_mae: 2.3963

Epoch 40/100

13/13 ————— **0s** 8ms/step - loss: 9.2558 - mae: 2.1869 - val_loss: 12.6237 - val_mae: 2.4448

Epoch 41/100

13/13 ————— **0s** 8ms/step - loss: 10.9504 - mae: 2.3415 - val_loss: 12.4824 - val_mae: 2.4041

Epoch 42/100

13/13 ————— **0s** 11ms/step - loss: 9.6774 - mae: 2.2578 - val_loss: 12.5157 - val_mae: 2.3991

Epoch 43/100

13/13 ————— **0s** 8ms/step - loss: 11.5649 - mae: 2.3402 - val_loss: 12.3560 - val_mae: 2.4115

Epoch 44/100

13/13 ————— **0s** 8ms/step - loss: 8.9539 - mae: 2.1521 - val_loss: 12.3741 - val_mae: 2.4153

Epoch 45/100

13/13 ————— **0s** 9ms/step - loss: 8.2015 - mae: 2.1457 - val_loss: 12.1208 - val_mae: 2.3555

Epoch 46/100

13/13 ————— **0s** 8ms/step - loss: 9.9797 - mae: 2.2662 - val_loss: 12.1381 - val_mae: 2.3701

Epoch 47/100

13/13 ————— **0s** 8ms/step - loss: 8.8198 - mae: 2.1529 - val_loss: 12.2269 - val_mae: 2.4122

Epoch 48/100

13/13 ————— **0s** 8ms/step - loss: 8.4290 - mae: 2.1315 - val_loss: 12.1853 - val_mae: 2.3905

Epoch 49/100

13/13 ————— **0s** 11ms/step - loss: 8.4449 - mae: 2.0870 - val_loss: 11.8539 - val_mae: 2.3324

Epoch 50/100

13/13 ————— **0s** 12ms/step - loss: 8.5006 - mae: 2.2061 - val_loss: 11.9640 - val_mae: 2.3704

Epoch 51/100

13/13 ————— **0s** 15ms/step - loss: 8.8283 - mae: 2.1345 - val_loss: 12.0963 - val_mae: 2.3760

Epoch 52/100

13/13 ————— **0s** 12ms/step - loss: 8.1949 - mae: 2.0867 - val_loss: 11.9829 - val_mae: 2.3850

Epoch 53/100

13/13 ————— **0s** 12ms/step - loss: 8.3074 - mae: 2.1288 - val_loss: 11.8918 - val_mae: 2.3708

Epoch 54/100

13/13 ————— **0s** 14ms/step - loss: 8.5944 - mae: 2.1000 - val_loss: 11.8053 - val_mae: 2.3275

Epoch 55/100

13/13 ————— **0s** 15ms/step - loss: 8.6307 - mae: 2.1742 - val_loss: 11.8994 - val_mae: 2.3766

Epoch 56/100

13/13 ————— **0s** 14ms/step - loss: 7.5287 - mae: 2.0152 - val_loss: 11.7821 - val_mae: 2.3272

Epoch 57/100

13/13 ————— **0s** 14ms/step - loss: 9.5536 - mae: 2.1461 - val_loss: 11.7908 - val_mae: 2.3460

Epoch 58/100

13/13 ————— **0s** 8ms/step - loss: 7.9760 - mae: 2.0952 - val_loss: 11.7289 - val_mae: 2.3405

Epoch 59/100

13/13 ————— **0s** 11ms/step - loss: 7.4103 - mae: 1.9821 - val_loss: 11.5598 - val_mae: 2.3343

Epoch 60/100

13/13 ————— **0s** 9ms/step - loss: 8.0281 - mae: 2.0649 - val_loss: 11.6326 - val_mae: 2.3222

Epoch 61/100

13/13 ————— **0s** 8ms/step - loss: 7.9537 - mae: 2.1234 - val_loss: 11.6840 - val_mae: 2.3373

Epoch 62/100

13/13 ————— **0s** 11ms/step - loss: 6.7830 - mae:
1.9117 - val_loss: 11.5146 - val_mae: 2.3250

Epoch 63/100

13/13 ————— **0s** 8ms/step - loss: 6.5071 - mae:
1.8985 - val_loss: 11.6098 - val_mae: 2.3411

Epoch 64/100

13/13 ————— **0s** 8ms/step - loss: 6.5164 - mae:
1.8591 - val_loss: 11.6063 - val_mae: 2.3413

Epoch 65/100

13/13 ————— **0s** 8ms/step - loss: 7.2535 - mae:
2.0678 - val_loss: 11.4727 - val_mae: 2.3506

Epoch 66/100

13/13 ————— **0s** 8ms/step - loss: 7.0746 - mae:
1.9760 - val_loss: 11.4880 - val_mae: 2.3260

Epoch 67/100

13/13 ————— **0s** 8ms/step - loss: 7.5375 - mae:
2.0352 - val_loss: 11.4362 - val_mae: 2.3249

Epoch 68/100

13/13 ————— **0s** 8ms/step - loss: 7.1914 - mae:
1.9469 - val_loss: 11.4533 - val_mae: 2.3224

Epoch 69/100

13/13 ————— **0s** 9ms/step - loss: 6.8427 - mae:
1.9217 - val_loss: 11.3773 - val_mae: 2.3217

Epoch 70/100

13/13 ————— **0s** 8ms/step - loss: 7.2902 - mae:
1.9790 - val_loss: 11.4590 - val_mae: 2.3406

Epoch 71/100

13/13 ————— **0s** 11ms/step - loss: 6.7016 - mae:
1.9035 - val_loss: 11.3007 - val_mae: 2.3049

Epoch 72/100

13/13 ————— **0s** 8ms/step - loss: 7.2743 - mae:
1.9617 - val_loss: 11.2552 - val_mae: 2.3023

Epoch 73/100

13/13 ————— **0s** 11ms/step - loss: 6.3395 - mae:
1.8849 - val_loss: 11.2838 - val_mae: 2.3039

Epoch 74/100

13/13 ————— **0s** 8ms/step - loss: 5.7177 - mae:
1.8060 - val_loss: 11.3000 - val_mae: 2.3359

Epoch 75/100

13/13 ————— **0s** 10ms/step - loss: 6.9417 - mae:
1.9170 - val_loss: 11.2139 - val_mae: 2.2928

Epoch 76/100

13/13 ————— **0s** 8ms/step - loss: 6.7695 - mae:
1.8807 - val_loss: 11.3194 - val_mae: 2.3076

Epoch 77/100

13/13 ————— **0s** 8ms/step - loss: 6.4793 - mae:
1.9218 - val_loss: 11.1718 - val_mae: 2.2917

Epoch 78/100

13/13 ————— **0s** 8ms/step - loss: 5.9527 - mae:
1.8150 - val_loss: 11.1246 - val_mae: 2.2861

Epoch 79/100

13/13 ————— **0s** 9ms/step - loss: 6.6951 - mae:
1.8398 - val_loss: 11.1160 - val_mae: 2.2774

Epoch 80/100

13/13 ————— **0s** 8ms/step - loss: 7.5368 - mae:
1.9240 - val_loss: 11.1665 - val_mae: 2.2982

Epoch 81/100

13/13 ————— **0s** 8ms/step - loss: 6.4592 - mae:
1.8762 - val_loss: 11.0936 - val_mae: 2.2619

Epoch 82/100

13/13 ————— **0s** 9ms/step - loss: 5.3143 - mae:
1.7145 - val_loss: 11.0148 - val_mae: 2.2724

Epoch 83/100

13/13 ————— **0s** 8ms/step - loss: 6.5988 - mae:
1.8990 - val_loss: 10.9220 - val_mae: 2.2246

Epoch 84/100

13/13 ————— **0s** 8ms/step - loss: 5.4782 - mae:
1.7403 - val_loss: 11.1440 - val_mae: 2.3064

Epoch 85/100

13/13 ————— **0s** 8ms/step - loss: 6.3924 - mae:
1.9266 - val_loss: 11.0227 - val_mae: 2.2435

Epoch 86/100

13/13 ————— **0s** 8ms/step - loss: 6.2494 - mae:
1.8472 - val_loss: 11.1810 - val_mae: 2.3017

Epoch 87/100

13/13 ————— **0s** 8ms/step - loss: 5.8213 - mae:
1.8355 - val_loss: 11.0506 - val_mae: 2.2427

Epoch 88/100

13/13 ————— **0s** 11ms/step - loss: 5.5436 - mae:
1.7404 - val_loss: 10.8650 - val_mae: 2.2267

Epoch 89/100

13/13 ————— **0s** 8ms/step - loss: 5.3958 - mae:
1.7563 - val_loss: 11.1224 - val_mae: 2.2834

Epoch 90/100

13/13 ————— **0s** 8ms/step - loss: 5.9054 - mae:
1.8215 - val_loss: 10.9026 - val_mae: 2.2327

Epoch 91/100

13/13 ————— **0s** 8ms/step - loss: 5.6878 - mae:
1.7825 - val_loss: 10.9910 - val_mae: 2.2707

Epoch 92/100

13/13 ————— **0s** 8ms/step - loss: 5.5403 - mae:
1.6760 - val_loss: 10.9581 - val_mae: 2.2239

Epoch 93/100

13/13 ————— **0s** 9ms/step - loss: 5.1754 - mae:
1.6417 - val_loss: 10.9196 - val_mae: 2.2451

Epoch 94/100

13/13 ————— **0s** 8ms/step - loss: 4.7708 - mae:
1.5968 - val_loss: 10.9063 - val_mae: 2.2444

Epoch 95/100

13/13 ————— **0s** 9ms/step - loss: 5.3026 - mae:
1.7182 - val_loss: 10.9286 - val_mae: 2.2356

Epoch 96/100

13/13 ————— **0s** 8ms/step - loss: 5.4537 - mae:
1.7007 - val_loss: 10.9806 - val_mae: 2.2173

Epoch 97/100

13/13 ————— **0s** 8ms/step - loss: 5.9074 - mae:
1.7838 - val_loss: 11.0709 - val_mae: 2.2828

Epoch 98/100

13/13 ————— **0s** 12ms/step - loss: 6.3417 - mae:
1.8338 - val_loss: 10.6875 - val_mae: 2.1934

Epoch 99/100

13/13 ————— **0s** 8ms/step - loss: 4.6122 - mae:
1.6040 - val_loss: 10.7461 - val_mae: 2.2067

Epoch 100/100

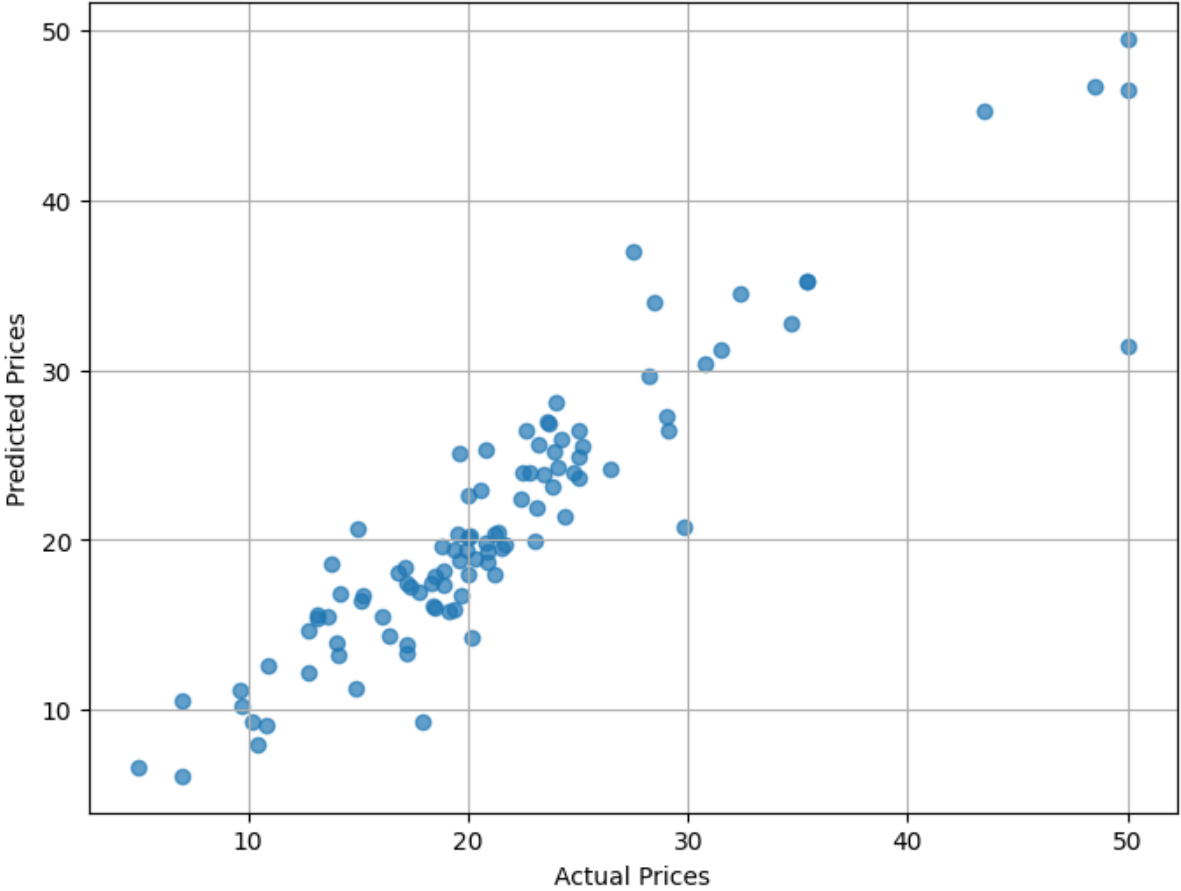
13/13 ————— **0s** 8ms/step - loss: 4.7816 - mae:
1.6578 - val_loss: 10.8373 - val_mae: 2.2065

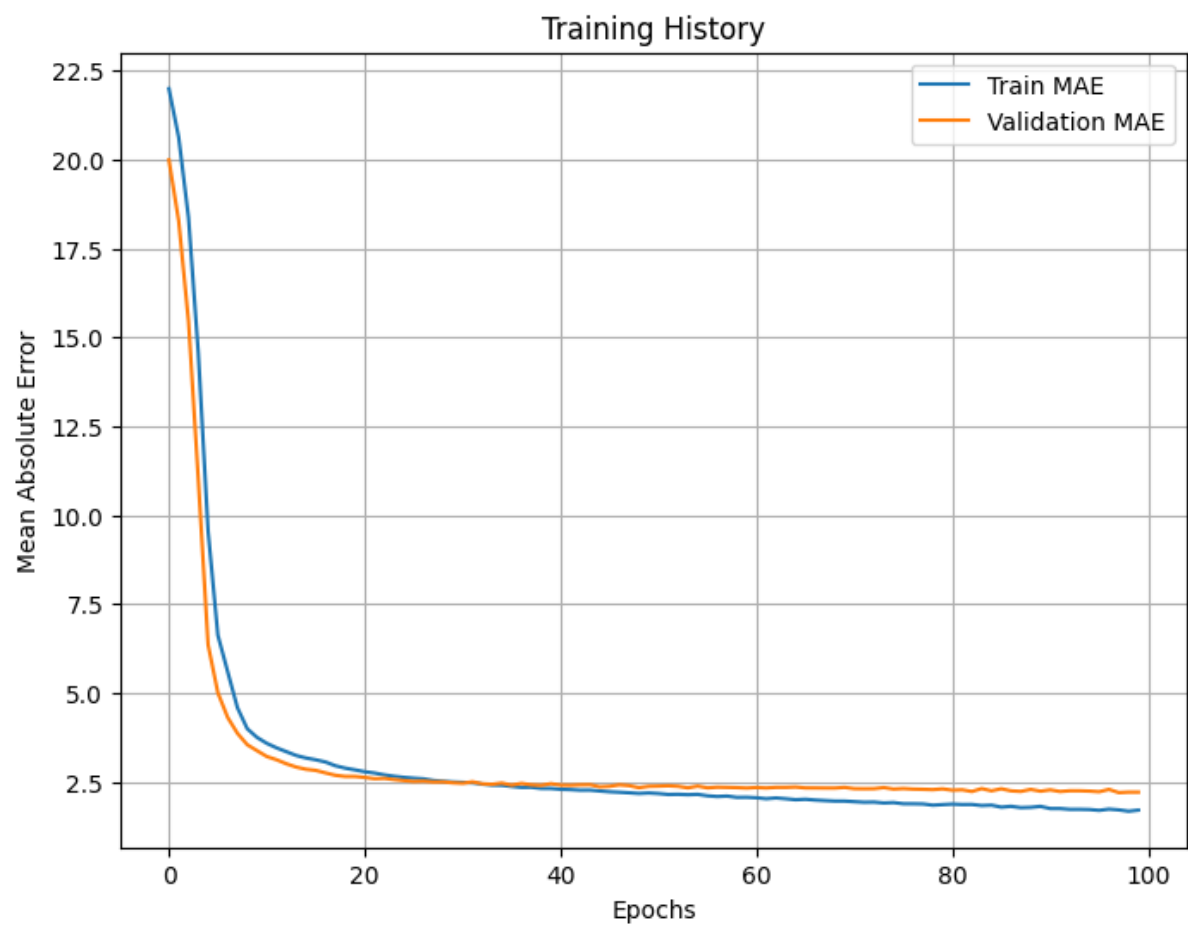
4/4 ————— **0s** 10ms/step - loss: 8.6214 - mae:
2.0805

Test MAE: 2.21

4/4 ————— **0s** 21ms/step

Actual vs Predicted Prices (Boston Housing)





PRACTICAL 2:

```
import tensorflow as tf

from tensorflow import keras

import numpy as np

import matplotlib.pyplot as plt


# Load the Fashion MNIST dataset

fashion_mnist = keras.datasets.fashion_mnist

(X_train, y_train), (X_test, y_test) = fashion_mnist.load_data()


# Class labels for Fashion MNIST

class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']


# Display dataset shape

print(f"Training Data Shape: {X_train.shape}, Testing Data Shape: {X_test.shape}")


# Normalize the dataset (scale pixel values between 0 and 1)

X_train = X_train / 255.0

X_test = X_test / 255.0


# Display some sample images

plt.figure(figsize=(10, 5))

for i in range(10):

    plt.subplot(2, 5, i + 1)

    plt.imshow(X_train[i], cmap='gray')

    plt.title(class_names[y_train[i]])

    plt.axis('off')
```



```
plt.show()
```

```
# Build the Deep Neural Network model
```

```
model = keras.Sequential([  
    keras.layers.Flatten(input_shape=(28, 28)), # Flatten 28x28 images  
    keras.layers.Dense(128, activation='relu'), # First hidden layer  
    keras.layers.Dense(64, activation='relu'), # Second hidden layer  
    keras.layers.Dense(10, activation='softmax') # Output layer (10 classes)  
])
```

```
# Compile the model
```

```
model.compile(optimizer='adam',  
              loss='sparse_categorical_crossentropy',  
              metrics=['accuracy'])
```

```
# Train the model
```

```
history = model.fit(X_train, y_train, epochs=10, validation_data=(X_test, y_test),  
                    batch_size=32, verbose=1)
```

```
# Evaluate the model
```

```
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=1)  
print(f"\nTest Accuracy: {test_acc:.4f}")
```

```
# Make predictions on test set
```

```
y_pred = model.predict(X_test)
```

```
# Display some test images with predictions
```

```
plt.figure(figsize=(10, 5))
```

```

for i in range(10):
    plt.subplot(2, 5, i + 1)
    plt.imshow(X_test[i], cmap='gray')
    plt.title(f"Pred: {class_names[np.argmax(y_pred[i])]} \n Actual: {class_names[y_test[i]]}")
    plt.axis('off')
plt.show()

```

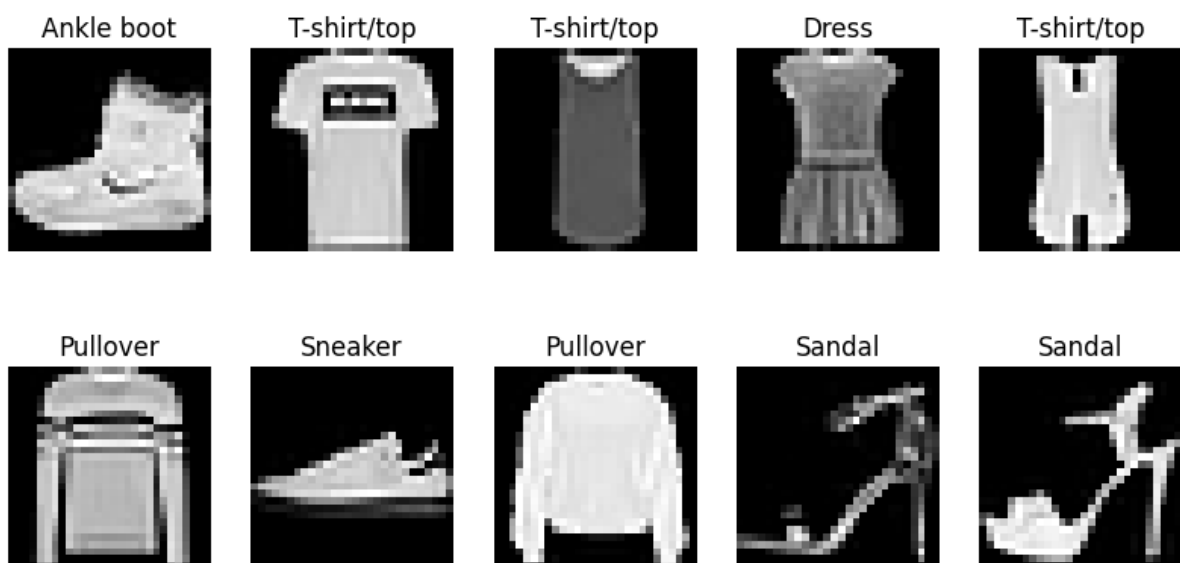
```

# Plot training history
plt.figure(figsize=(8, 6))
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.title("Training History")
plt.grid(True)
plt.show()

```

OUTPUT:

Training Data Shape: (60000, 28, 28), Testing Data Shape: (10000, 28, 28)



Epoch 1/10

1875/1875 ————— **10s** 5ms/step - accuracy:
0.7797 - loss: 0.6282 - val_accuracy: 0.8403 - val_loss: 0.4299

Epoch 2/10

1875/1875 ————— **9s** 5ms/step - accuracy: 0.8619
- loss: 0.3770 - val_accuracy: 0.8619 - val_loss: 0.3829

Epoch 3/10

1875/1875 ————— **7s** 4ms/step - accuracy: 0.8760
- loss: 0.3329 - val_accuracy: 0.8685 - val_loss: 0.3689

Epoch 4/10

1875/1875 ————— **11s** 4ms/step - accuracy:
0.8882 - loss: 0.3028 - val_accuracy: 0.8485 - val_loss: 0.4119

Epoch 5/10

1875/1875 ————— **11s** 5ms/step - accuracy:
0.8948 - loss: 0.2845 - val_accuracy: 0.8700 - val_loss: 0.3600

Epoch 6/10

1875/1875 ————— **10s** 5ms/step - accuracy:
0.8953 - loss: 0.2764 - val_accuracy: 0.8780 - val_loss: 0.3443

Epoch 7/10

1875/1875 ————— **9s** 4ms/step - accuracy: 0.9017
- loss: 0.2599 - val_accuracy: 0.8838 - val_loss: 0.3270

Epoch 8/10

1875/1875 ————— **10s** 4ms/step - accuracy:
0.9066 - loss: 0.2483 - val_accuracy: 0.8806 - val_loss: 0.3366

Epoch 9/10

1875/1875 ————— **9s** 5ms/step - accuracy: 0.9092
- loss: 0.2389 - val_accuracy: 0.8806 - val_loss: 0.3389

Epoch 10/10

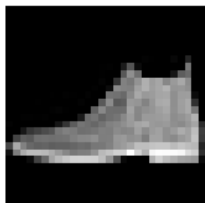
1875/1875 ————— **10s** 5ms/step - accuracy:
0.9116 - loss: 0.2305 - val_accuracy: 0.8826 - val_loss: 0.3315

313/313 ————— 1s 2ms/step - accuracy: 0.8824 -
loss: 0.3318

Test Accuracy: 0.8826

313/313 ————— 1s 2ms/step

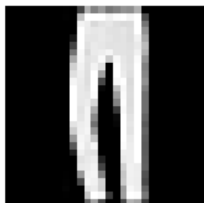
Pred: Ankle boot
Actual: Ankle boot



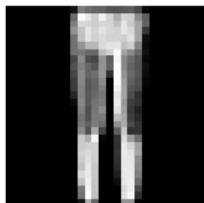
Pred: Pullover
Actual: Pullover



Pred: Trouser
Actual: Trouser



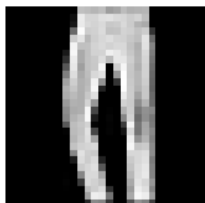
Pred: Trouser
Actual: Trouser



Pred: Shirt
Actual: Shirt



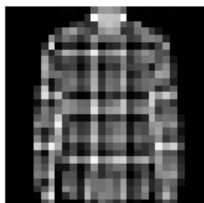
Pred: Trouser
Actual: Trouser



Pred: Coat
Actual: Coat



Pred: Shirt
Actual: Shirt



Pred: Sandal
Actual: Sandal



Pred: Sneaker
Actual: Sneaker



