

Task 3: Multimodal ML Housing Price Prediction Using Image Tabular Data**MULTINOMIAL HOUSE PRICE PREDICTION**

```

import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow.keras import layers, models, Input, Model
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.model_selection import train_test_split

# 1. Generate dummy image data (e.g., 100 images of size 64x64 RGB)
num_samples = 100
image_height = 64
image_width = 64
image_channels = 3

# Dummy image data (simulating house photos)
image_data = np.random.rand(num_samples, image_height, image_width, image_channels)

# 2. Generate dummy tabular data (e.g., 5 features like area, rooms, etc.)
tabular_data = np.random.rand(num_samples, 5)

# 3. Target variable (house prices in lakhs)
prices = np.random.randint(30, 150, size=(num_samples,)) # prices between 30-150 lakhs

# 4. Train-test split
X_img_train, X_img_test, X_tab_train, X_tab_test, y_train, y_test = train_test_split(
    image_data, tabular_data, prices, test_size=0.2, random_state=42
)

# 5. CNN for image processing
image_input = Input(shape=(image_height, image_width, image_channels))
x = layers.Conv2D(16, (3, 3), activation='relu')(image_input)
x = layers.MaxPooling2D((2, 2))(x)
x = layers.Conv2D(32, (3, 3), activation='relu')(x)
x = layers.MaxPooling2D((2, 2))(x)
x = layers.Flatten()(x)
x = layers.Dense(64, activation='relu')(x)
image_output = layers.Dense(32, activation='relu')(x)

# 6. MLP for tabular data
tabular_input = Input(shape=(tabular_data.shape[1],))
y = layers.Dense(32, activation='relu')(tabular_input)
tabular_output = layers.Dense(16, activation='relu')(y)

# 7. Combine both features
combined = layers.concatenate([image_output, tabular_output])
z = layers.Dense(64, activation='relu')(combined)
z = layers.Dense(32, activation='relu')(z)
final_output = layers.Dense(1)(z)

# 8. Define the full model
model = Model(inputs=[image_input, tabular_input], outputs=final_output)
model.compile(optimizer='adam', loss='mse')

# 9. Train the model
model.fit([X_img_train, X_tab_train], y_train, epochs=10, batch_size=8, verbose=1)

# 10. Evaluate
predictions = model.predict([X_img_test, X_tab_test])
mae = mean_absolute_error(y_test, predictions)
rmse = np.sqrt(mean_squared_error(y_test, predictions))

print(f"\n📊 MAE (Mean Absolute Error): {mae:.2f}")
print(f"📊 RMSE (Root Mean Squared Error): {rmse:.2f}")

```

```

Epoch 1/10
10/10 — 4s 27ms/step - loss: 8226.0950
Epoch 2/10
10/10 — 0s —
Epoch 3/10
10/10 — 0s 28ms/step - loss: 1628.0596
Epoch 4/10



```

What can I help you build?

```

10/10 ————— 0s 27ms/step - loss: 1281.7703
Epoch 5/10
10/10 ————— 0s 30ms/step - loss: 1397.0870
Epoch 6/10
10/10 ————— 0s 27ms/step - loss: 1331.8907
Epoch 7/10
10/10 ————— 0s 27ms/step - loss: 1220.8816
Epoch 8/10
10/10 ————— 0s 28ms/step - loss: 1488.7830
Epoch 9/10
10/10 ————— 0s 26ms/step - loss: 1153.2782
Epoch 10/10
10/10 ————— 0s 27ms/step - loss: 1464.6940
1/1 ————— 0s 138ms/step

```

 MAE (Mean Absolute Error): 31.49
 RMSE (Root Mean Squared Error): 34.79

```

from sklearn.datasets import load_breast_cancer
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load built-in dataset
data = load_breast_cancer()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['target'] = data.target

# Basic info
print(df.shape)
print(df.info())
print(df.describe())

# Nulls check
print(df.isnull().sum())

# Target distribution
sns.countplot(x='target', data=df)
plt.title("Target Distribution")
plt.show()

# Heatmap
sns.heatmap(df.corr(), cmap='viridis')
plt.title("Correlation Heatmap")
plt.show()

# Histograms
df.hist(figsize=(12, 10))
plt.tight_layout()
plt.show()

```



(569, 31)

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 569 entries, 0 to 568

Data columns (total 31 columns):

#	Column	Non-Null Count	Dtype
0	mean radius	569 non-null	float64
1	mean texture	569 non-null	float64
2	mean perimeter	569 non-null	float64
3	mean area	569 non-null	float64
4	mean smoothness	569 non-null	float64
5	mean compactness	569 non-null	float64
6	mean concavity	569 non-null	float64
7	mean concave points	569 non-null	float64
8	mean symmetry	569 non-null	float64
9	mean fractal dimension	569 non-null	float64
10	radius error	569 non-null	float64
11	texture error	569 non-null	float64
12	perimeter error	569 non-null	float64
13	area error	569 non-null	float64
14	smoothness error	569 non-null	float64
15	compactness error	569 non-null	float64
16	concavity error	569 non-null	float64
17	concave points error	569 non-null	float64
18	symmetry error	569 non-null	float64
19	fractal dimension error	569 non-null	float64
20	worst radius	569 non-null	float64
21	worst texture	569 non-null	float64
22	worst perimeter	569 non-null	float64
23	worst area	569 non-null	float64
24	worst smoothness	569 non-null	float64
25	worst compactness	569 non-null	float64
26	worst concavity	569 non-null	float64
27	worst concave points	569 non-null	float64
28	worst symmetry	569 non-null	float64
29	worst fractal dimension	569 non-null	float64
30	target	569 non-null	int64

dtypes: float64(30), int64(1)

memory usage: 137.9 KB

None

	mean radius	mean texture	mean perimeter	mean area \
count	569.000000	569.000000	569.000000	569.000000
mean	14.127292	19.289649	91.969033	654.889104
std	3.524049	4.301036	24.298981	351.914129
min	6.981000	9.710000	43.790000	143.500000
25%	11.700000	16.170000	75.170000	420.300000
50%	13.370000	18.840000	86.240000	551.100000
75%	15.780000	21.800000	104.100000	782.700000
max	28.110000	39.280000	188.500000	2501.000000

	mean smoothness	mean compactness	mean concavity	mean concave points \
count	569.000000	569.000000	569.000000	569.000000
mean	0.096360	0.104341	0.088799	0.048919
std	0.014064	0.052813	0.079720	0.038803
min	0.052630	0.019380	0.000000	0.000000
25%	0.086370	0.064920	0.029560	0.020310
50%	0.095870	0.092630	0.061540	0.033500
75%	0.105300	0.130400	0.130700	0.074000
max	0.163400	0.345400	0.426800	0.201200

	mean symmetry	mean fractal dimension	... worst texture \
count	569.000000	569.000000	... 569.000000
mean	0.181162	0.062798	... 25.677223
std	0.027414	0.007060	... 6.146258
min	0.106000	0.049960	... 12.020000
25%	0.161900	0.057700	... 21.080000
50%	0.179200	0.061540	... 25.410000
75%	0.195700	0.066120	... 29.720000
max	0.304000	0.097440	... 49.540000

	worst perimeter	worst area	worst smoothness	worst compactness \
count	569.000000	569.000000	569.000000	569.000000
mean	107.261213	880.583128	0.132369	0.254265
std	33.602542	569.356993	0.022832	0.157336
min	50.410000	185.200000	0.071170	0.027290
25%	84.110000	515.300000	0.116600	0.147200
50%	97.660000	686.500000	0.131300	0.211900
75%	125.400000	1084.000000	0.146000	0.339100
max	251.200000	4254.000000	0.222600	1.058000

	worst concavity	worst concave points	worst symmetry \
count	569.000000	569.000000	569.000000
mean	0.272188	0.114606	0.290076
std	0.208624	0.065732	0.061867
min	0.000000	0.000000	0.000000