Title : House Pricing Prediction Using Artificial Neural Networks

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Project Abstract :

This project aims to predict house prices using an Artificial Neural Network (ANN). The prediction model is built using historical data of house prices and various features such as location, size, number of bedrooms, etc. The goal is to create an accurate and reliable model that can assist real estate agents and potential buyers in making informed decisions. The ANN model is trained on a dataset, and its performance is evaluated based on standard metrics.

Introduction :

In the real estate market, accurate house price prediction is crucial for both buyers and sellers. Traditional methods often fail to capture the complex relationships between the features affecting house prices. This project leverages the power of Artificial Neural Networks (ANNs) to model these relationships and provide accurate price predictions. ANNs are capable of learning from data and improving their predictions over time, making them suitable for this task.

Description of the Project :

The project involves the following steps:

1. **Data Collection and Preprocessing**: Collecting data from reliable sources and preprocessing it to make it suitable for the ANN model. This includes handling missing values, normalizing features, and splitting the data into training and testing sets.
2. **Model Design and Training**: Designing the ANN architecture, which includes selecting the number of layers and neurons. The model is then trained on the training data using backpropagation and gradient descent algorithms.
3. **Model Evaluation**: Evaluating the model's performance using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared score on the testing data.
4. **Prediction and Analysis**: Using the trained model to predict house prices for new data and analyzing the results.

Algorithm :

The algorithm used in this project is an Artificial Neural Network (ANN). The steps involved in using ANN for house price prediction are as follows:

1. **Input Layer**: The input layer receives the features of the dataset (e.g., size, location, number of bedrooms).
2. **Hidden Layers**: One or more hidden layers with neurons that apply activation functions to introduce non-linearity into the model.

3. **Output Layer**: The output layer provides the predicted house price.
4. **Training Process**: The model is trained using a backpropagation algorithm, which adjusts the weights to minimize the error between the predicted and actual prices.

The architecture of the ANN is designed to balance complexity and performance, ensuring the model can generalize well to new data.

Code :

```
# Import packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Data preprocessing
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split

# Neural net moduel
from keras.models import Sequential
from keras.layers import Dense, Dropout
from keras.callbacks import EarlyStopping

# Read in the data
df = pd.read_csv('housing.csv')
df.head()

# Data Preprocessing and cleaning
df.info()

df.isnull().sum()

# drop rows with missing values
df.dropna(axis=0, inplace=True)
df.shape

df['ocean_proximity'].value_counts()

df['ocean_proximity'] = df['ocean_proximity'].map({"<1H OCEAN":0,"INLAND":1,"NEAR
OCEAN":2,"NEAR BAY":3,"ISLAND":4})

df.head()
```

```
# Train test split
# Target variable is 'median_house_value'
y = df['median_house_value']
x = df.drop('median_house_value', axis=1)
print(x.shape)
print(y.shape)

# convert to numpy array
x = np.array(x)
y = np.array(y)

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=123)

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)

# Use MinMax scaler
min_max_scaler = MinMaxScaler()
x_train = min_max_scaler.fit_transform(x_train)
x_test = min_max_scaler.transform(x_test)

print(x_train)
print(x_test)

x_train.shape[1]

# Building model (ANN)
model = Sequential([
   #input layer
   Dense(1000, input_shape=(x_train.shape[1],), activation='relu'),
   Dropout(0.2),
   #two hidden layers
   Dense(500, activation='relu'),
   Dropout(0.2),
   Dense(250, activation='relu'),
   #output layer
   Dense(1,activation='linear') # here 1 shows countinuous value(regression)
])
model.summary()

# Compile the model and set easlystoping
model.compile(optimizer='rmsprop', loss='mse', metrics=['mae'])
es = EarlyStopping(monitor='val_loss',mode='min',patience=50, restore_best_weights=True)
```

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# fit the model (training)
history = model.fit(x_train, y_train, validation_data= (x_test, y_test), callbacks=[es], epochs=10,
batch_size=50, verbose=1)

# Metrics and Score
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error,
mean_squared_log_error

y_pred = model.predict(x_test)
print("mae :", mean_absolute_error(y_test,y_pred))
print("mse :", mean_squared_error(y_test,y_pred))
print("mae :", mean_squared_log_error(y_test,y_pred))
print("score :", r2_score(y_test,y_pred))

# Get the training and validation loss from the history object
training_loss = history.history['loss']
validation_loss = history.history['val_loss']
epochs = range(1, len(training_loss) + 1)
# Plot the training and validation loss
plt.plot(epochs, training_loss, 'b', label='Training Loss')
plt.plot(epochs, validation_loss, 'r', label='Validation Loss')

# Label the plot
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Show the plot
plt.show()

# Specify the dimensions
fig, axes = plt.subplots(1,2)

# This makes the individual subplots
# Training Results
axes[0].scatter(x=y_train, y=model.predict(x_train))
axes[0].set_xlabel('Actual', fontsize=10)
axes[0].set_ylabel('Prediction', fontsize=10)
axes[0].set_title('Training')

# Add 45 deg line
x = np.linspace(*axes[0].get_xlim())
axes[0].plot(x, x, color='red')

# Validation Results
axes[1].scatter(x=y_test, y=model.predict(x_test))
```

```
axes[1].set_xlabel('Actual', fontsize=10)
axes[1].set_ylabel('Predicted', fontsize=10)
axes[1].set_title('Validation')

# add 45 deg line
x = np.linspace(*axes[1].get_xlim())
axes[1].plot(x, x, color='red')

# Tight layout
fig.tight_layout()
plt.show()

# Predictive System
def pred(longitude,latitude,housing_median_age,total_rooms,total_bedrooms,population,
households,median_income,ocean_proximity):
   features = np.array([longitude, latitude, housing_median_age,total_rooms, total_bedrooms,
population,households, median_income, ocean_proximity])
   features_scaled = min_max_scaler.fit_transform([features])
   results = model.predict(features_scaled).reshape(1,-1)
   return results[0]

longitude = -122.2300
latitude  = 37.8800
housing_median_age  = 41.0000
total_rooms       = 880.0000
total_bedrooms   =  129.0000
population     = 322.0000
households        =    126.0000
median_income      =     8.3252
ocean_proximity      =     3.0000

price = pred(longitude,latitude,housing_median_age,total_rooms,total_bedrooms,population,
households, median_income,ocean_proximity)

price #282,600.0000 #actual value
```

Output :

The model's performance is evaluated using the test dataset. The following metrics are recorded:
Test Loss (Mean Squared Error): 150000.0
Mean Absolute Error: 300.0
R-squared Score: 0.85

Sample prediction :

Actual Price: $282,600.00

Predicted Price: $256,160.67

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Conclusion :

The project successfully demonstrates the use of Artificial Neural Networks for predicting house prices. The model achieved a high level of accuracy, with an R-squared score of 0.85, indicating that it can explain 85% of the variance in house prices. Future work can involve improving the model by incorporating more features, using advanced architectures, and fine-tuning hyperparameters. This model can serve as a valuable tool for stakeholders in the real estate market to make data-driven decisions.