실제 데이터로 만들어 보는 모델

1. 데이터 파악하기

In [3]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt
import seaborn as sns

import pandas as pd
import numpy as np

# 집 값 데이터를 불러옵니다.
df = pd.read_csv("./data/house_train.csv")

# 데이터를 미리 살펴보겠습니다.
df
```

Out[3]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	MnPrv
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	GdPrv
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN

1460 rows × 81 columns

In [4]:

```
# 데이터가 어떤 유형으로 이루어져 있는지 알아봅니다.
df.dtypes
```

```
Out[4]: Id                 int64
        MSSubClass         int64
        MSZoning          object
        LotFrontage      float64
        LotArea            int64
                          ...
        MoSold             int64
        YrSold             int64
        SaleType          object
        SaleCondition     object
        SalePrice          int64
        Length: 81, dtype: object
```

2. 결측치, 카테고리 변수 처리하기

```
In [6]: # 속성별로 결측치가 몇 개인지 확인합니다.
        df.isnull().sum().sort_values(ascending=False).head(20)
```

```
Out[6]: PoolQC          1453
        MiscFeature     1406
        Alley           1369
        Fence           1179
        MasVnrType       872
        FireplaceQu      690
        LotFrontage      259
        GarageYrBlt       81
        GarageCond        81
        GarageType        81
        GarageFinish      81
        GarageQual        81
        BsmtFinType2      38
        BsmtExposure      38
        BsmtQual          37
        BsmtCond          37
        BsmtFinType1      37
        MasVnrArea         8
        Electrical         1
        Id                 0
        dtype: int64
```

In [7]:
```python
# 카테고리형 변수를 0과 1로 이루어진 변수로 바꾸어 줍니다.
df = pd.get_dummies(df)

# 결측치를 전체 칼럼의 평균으로 대체하여 채워줍니다.
df = df.fillna(df.mean())


# 업데이트된 데이터 프레임을 출력해봅니다.
df
```

Out[7]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	SaleT
0	1	60	65.0	8450	7	5	2003	2003	196.0	706	...	
1	2	20	80.0	9600	6	8	1976	1976	0.0	978	...	
2	3	60	68.0	11250	7	5	2001	2002	162.0	486	...	
3	4	70	60.0	9550	7	5	1915	1970	0.0	216	...	
4	5	60	84.0	14260	8	5	2000	2000	350.0	655	...	
...	...	...	...	...	...	...	...	...	...	...	...	
1455	1456	60	62.0	7917	6	5	1999	2000	0.0	0	...	
1456	1457	20	85.0	13175	6	6	1978	1988	119.0	790	...	
1457	1458	70	66.0	9042	7	9	1941	2006	0.0	275	...	
1458	1459	20	68.0	9717	5	6	1950	1996	0.0	49	...	
1459	1460	20	75.0	9937	5	6	1965	1965	0.0	830	...	

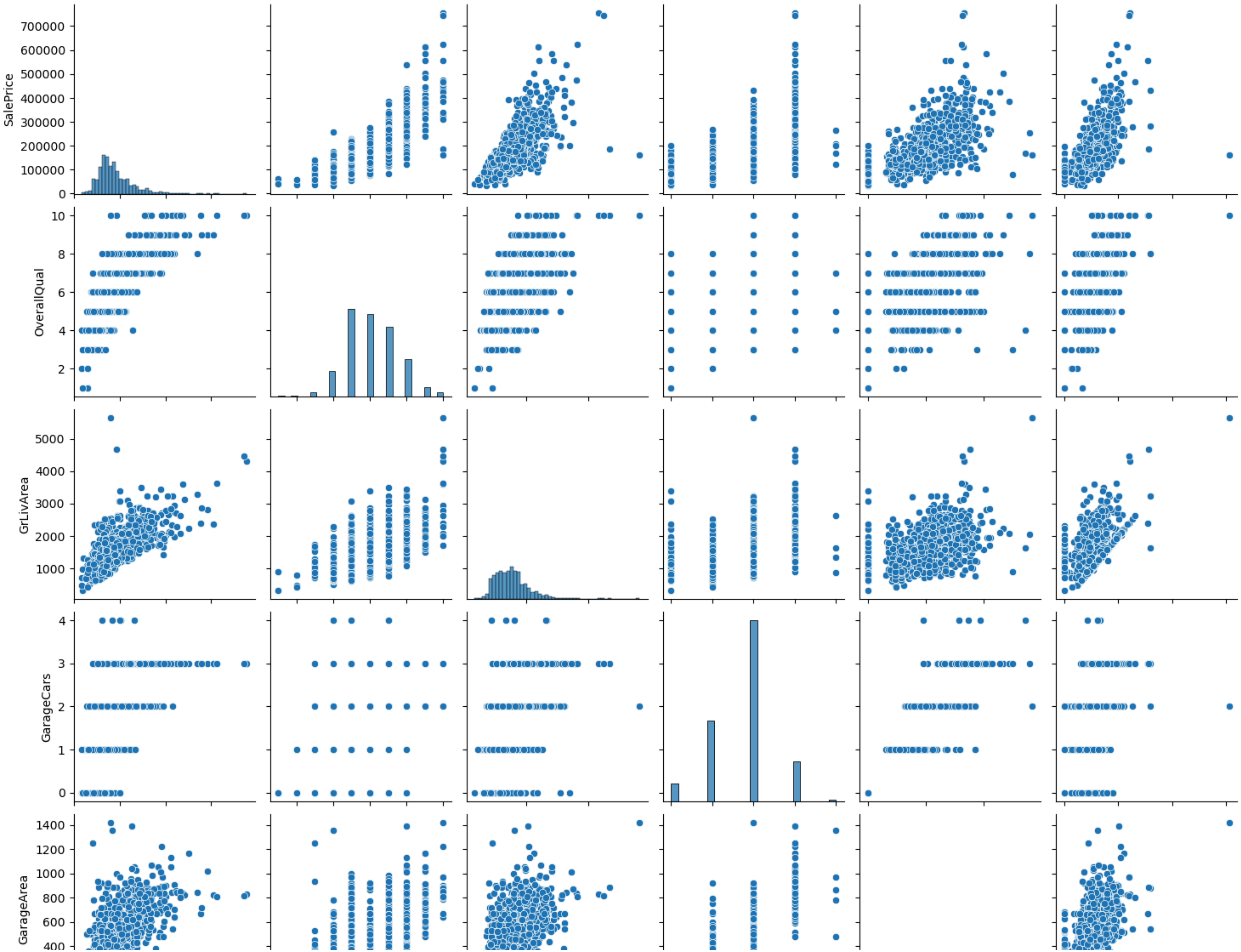
1460 rows × 289 columns

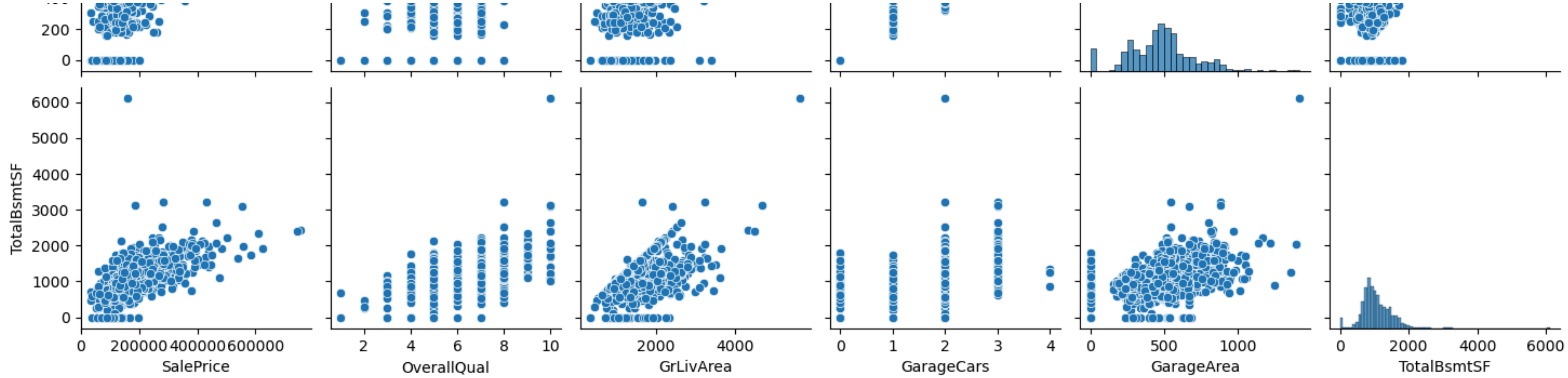
3. 속성별 관련도 추출하기

In [9]:
```python
# 데이터 사이의 상관 관계를 저장합니다.
df_corr=df.corr()

# 집 값과 관련이 큰 것부터 순서대로 저장합니다.
df_corr_sort=df_corr.sort_values('SalePrice', ascending=False)


# 집 값과 관련도가 가장 큰 10개의 속성들을 출력합니다.
df_corr_sort['SalePrice'].head(10)
```

Out[9]:
```
SalePrice       1.000000
OverallQual     0.790982
GrLivArea       0.708624
GarageCars      0.640409
GarageArea      0.623431
TotalBsmtSF     0.613581
1stFlrSF        0.605852
FullBath        0.560664
BsmtQual_Ex     0.553105
TotRmsAbvGrd    0.533723
Name: SalePrice, dtype: float64
```

In [10]:
```python
# 집 값과 관련도가 가장 높은 속성들을 추출해서 상관도 그래프를 그려봅니다.
cols=['SalePrice','OverallQual','GrLivArea','GarageCars','GarageArea','TotalBsmtSF']
sns.pairplot(df[cols])
plt.show();
```


SalePrice
700000
600000
500000
400000
300000
200000
100000
0
OverallQual
10
8
6
4
2
GrLivArea
5000
4000
3000
2000
1000
GarageCars
4
3
2
1
0
GarageArea
1400
1200
1000
800
600
400



4. 주택 가격 예측 모델

In [12]:
```
# 집 값을 제외한 나머지 열을 저장합니다.
cols_train=['OverallQual','GrLivArea','GarageCars','GarageArea','TotalBsmtSF']
X_train_pre = df[cols_train]

# 집 값을 저장합니다.
y = df['SalePrice'].values
```

In [13]:
```
# 전체의 80%를 학습셋으로, 20%를 테스트셋으로 지정합니다.
X_train, X_test, y_train, y_test = train_test_split(X_train_pre, y,
                                                     test_size=0.2)
```

In [14]:
```
X_train
```

Out[14]:

	OverallQual	GrLivArea	GarageCars	GarageArea	TotalBsmtSF
1026	5	1264	2	461	1268
1144	4	924	1	280	672
815	7	1661	2	598	1649
1422	6	848	2	420	848
844	5	1416	3	720	876
...	...	...	...	...	...
999	7	1208	2	632	1187
199	8	1713	3	856	1713
273	6	1632	1	338	1240
945	5	1869	2	456	1088
921	5	2200	0	0	1272

1168 rows × 5 columns

In [15]:

```
X_train.shape[1]
```

Out[15]: 5

In [16]:

```
X_train.shape[0]
```

Out[16]: 1168

In [17]:

```
# 모델의 구조를 설정합니다.
model = Sequential()
model.add(Dense(10, input_dim=X_train.shape[1], activation='relu'))
model.add(Dense(30, activation='relu'))
model.add(Dense(40, activation='relu'))
model.add(Dense(1))
model.summary()
```

```
# 모델을 실행합니다.
model.compile(optimizer ='adam', loss = 'mean_squared_error')

# 20회 이상 결과가 향상되지 않으면 자동으로 중단되게끔 합니다.
early_stopping_callback = EarlyStopping(monitor='val_loss', patience=20)

# 모델의 이름을 정합니다.
modelpath="./data/model/house.keras"

# 최적화 모델을 업데이트하고 저장합니다.
checkpointer = ModelCheckpoint(filepath=modelpath, monitor='val_loss', verbose=0,
                               save_best_only=True)

# 실행 관련 설정을 하는 부분입니다. 전체의 20%를 검증셋으로 설정합니다.
history = model.fit(X_train, y_train, validation_split=0.25, epochs=2000, batch_size=32,
                    callbacks=[early_stopping_callback, checkpointer])
```

```
C:\Users\user\AppData\Roaming\Python\Python312\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `in
put_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first la
yer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 10)	60
dense_1 (Dense)	(None, 30)	330
dense_2 (Dense)	(None, 40)	1,240
dense_3 (Dense)	(None, 1)	41

Total params: 1,671 (6.53 KB)

Trainable params: 1,671 (6.53 KB)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 1s 8ms/step - loss: 40621993984.0000 - val_loss: 43452116992.0000
Epoch 2/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 40898375680.0000 - val_loss: 43243679744.0000
Epoch 3/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 40762560512.0000 - val_loss: 42638688256.0000
Epoch 4/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 36262166528.0000 - val_loss: 40827453440.0000
Epoch 5/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 36694118400.0000 - val_loss: 36163764224.0000
Epoch 6/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 30310084608.0000 - val_loss: 25992732672.0000
Epoch 7/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 19231047680.0000 - val_loss: 11992303616.0000
Epoch 8/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 7531496448.0000 - val_loss: 3789261568.0000
Epoch 9/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2376219136.0000 - val_loss: 3004286976.0000
Epoch 10/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2731359488.0000 - val_loss: 3007006976.0000
Epoch 11/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2033474944.0000 - val_loss: 3015180032.0000
Epoch 12/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2044061824.0000 - val_loss: 3005108480.0000
Epoch 13/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2267543552.0000 - val_loss: 3017346304.0000
Epoch 14/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2131735296.0000 - val_loss: 2966912000.0000
Epoch 15/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1927731584.0000 - val_loss: 2982296320.0000
Epoch 16/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2128701440.0000 - val_loss: 2979170048.0000
Epoch 17/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2209284864.0000 - val_loss: 2953841664.0000
Epoch 18/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2310153216.0000 - val_loss: 2934682880.0000
Epoch 19/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 2735981824.0000 - val_loss: 2924459776.0000
Epoch 20/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2169550080.0000 - val_loss: 2913668096.0000
Epoch 21/2000
```

```
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1923350272.0000 - val_loss: 2900907520.0000
Epoch 22/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1940629120.0000 - val_loss: 2941391360.0000
Epoch 23/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2264622336.0000 - val_loss: 2912863488.0000
Epoch 24/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 3540995328.0000 - val_loss: 2872023296.0000
Epoch 25/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1905636224.0000 - val_loss: 2894430464.0000
Epoch 26/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2620091904.0000 - val_loss: 2860761088.0000
Epoch 27/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1906577024.0000 - val_loss: 2862200064.0000
Epoch 28/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1881555200.0000 - val_loss: 2884243712.0000
Epoch 29/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2046958976.0000 - val_loss: 2856197888.0000
Epoch 30/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2736414976.0000 - val_loss: 2850432768.0000
Epoch 31/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1911504000.0000 - val_loss: 2853706752.0000
Epoch 32/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2749214208.0000 - val_loss: 2830329600.0000
Epoch 33/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2204791296.0000 - val_loss: 2831790336.0000
Epoch 34/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2785071360.0000 - val_loss: 2839087872.0000
Epoch 35/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1656902144.0000 - val_loss: 2818358272.0000
Epoch 36/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1822146816.0000 - val_loss: 2840817152.0000
Epoch 37/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2379496448.0000 - val_loss: 2827160832.0000
Epoch 38/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1852700672.0000 - val_loss: 2808710144.0000
Epoch 39/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2055969536.0000 - val_loss: 2847215872.0000
Epoch 40/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 2347538688.0000 - val_loss: 2802291968.0000
Epoch 41/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2323688448.0000 - val_loss: 2818152448.0000
```

```
Epoch 42/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2936237568.0000 - val_loss: 2797662976.0000
Epoch 43/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2442640640.0000 - val_loss: 2799649536.0000
Epoch 44/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2034462336.0000 - val_loss: 2806695680.0000
Epoch 45/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2532009472.0000 - val_loss: 2807466496.0000
Epoch 46/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1805865344.0000 - val_loss: 2776421888.0000
Epoch 47/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1917146752.0000 - val_loss: 2801520896.0000
Epoch 48/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2618306816.0000 - val_loss: 2788278016.0000
Epoch 49/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2046962688.0000 - val_loss: 2774238208.0000
Epoch 50/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2288008448.0000 - val_loss: 2819094272.0000
Epoch 51/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2449957888.0000 - val_loss: 2779755008.0000
Epoch 52/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2833268736.0000 - val_loss: 2767728128.0000
Epoch 53/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2641238016.0000 - val_loss: 2793065984.0000
Epoch 54/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2134853376.0000 - val_loss: 2777962240.0000
Epoch 55/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2079066624.0000 - val_loss: 2794941440.0000
Epoch 56/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2357879040.0000 - val_loss: 2779915520.0000
Epoch 57/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2940577024.0000 - val_loss: 2758164480.0000
Epoch 58/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 2166676992.0000 - val_loss: 2771896832.0000
Epoch 59/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1989050368.0000 - val_loss: 2766094592.0000
Epoch 60/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2919197952.0000 - val_loss: 2750511616.0000
Epoch 61/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 3476622848.0000 - val_loss: 2743190528.0000
Epoch 62/2000
```

```
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2207616256.0000 - val_loss: 2771771392.0000
Epoch 63/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2276735232.0000 - val_loss: 2772071680.0000
Epoch 64/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 3560146944.0000 - val_loss: 2740962816.0000
Epoch 65/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2539158784.0000 - val_loss: 2754073088.0000
Epoch 66/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1968413952.0000 - val_loss: 2769428480.0000
Epoch 67/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 3195341312.0000 - val_loss: 2742729984.0000
Epoch 68/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2415390208.0000 - val_loss: 2742373376.0000
Epoch 69/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1825295232.0000 - val_loss: 2736502016.0000
Epoch 70/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1928726272.0000 - val_loss: 2764627712.0000
Epoch 71/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2625816064.0000 - val_loss: 2747321344.0000
Epoch 72/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2138827392.0000 - val_loss: 2760314624.0000
Epoch 73/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1853707520.0000 - val_loss: 2759399168.0000
Epoch 74/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2282824704.0000 - val_loss: 2769386752.0000
Epoch 75/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1942260480.0000 - val_loss: 2747090432.0000
Epoch 76/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2193025280.0000 - val_loss: 2750268416.0000
Epoch 77/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 3031455232.0000 - val_loss: 2734267904.0000
Epoch 78/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1731789696.0000 - val_loss: 2734811136.0000
Epoch 79/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1968298368.0000 - val_loss: 2743973120.0000
Epoch 80/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1919640448.0000 - val_loss: 2786626304.0000
Epoch 81/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 2199901696.0000 - val_loss: 2730529024.0000
Epoch 82/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1800106880.0000 - val_loss: 2734356992.0000
```

```
Epoch 83/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 2101043712.0000 - val_loss: 2765747712.0000
Epoch 84/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1893531136.0000 - val_loss: 2730318336.0000
Epoch 85/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2417772032.0000 - val_loss: 2726030592.0000
Epoch 86/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2013420416.0000 - val_loss: 2735704064.0000
Epoch 87/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1967384832.0000 - val_loss: 2744951552.0000
Epoch 88/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2325751552.0000 - val_loss: 2733280256.0000
Epoch 89/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 3119764992.0000 - val_loss: 2722760960.0000
Epoch 90/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1799378048.0000 - val_loss: 2723547648.0000
Epoch 91/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2389433088.0000 - val_loss: 2753713408.0000
Epoch 92/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2348241920.0000 - val_loss: 2726230272.0000
Epoch 93/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2018135808.0000 - val_loss: 2737978624.0000
Epoch 94/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2880532992.0000 - val_loss: 2733359872.0000
Epoch 95/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2604578816.0000 - val_loss: 2718259968.0000
Epoch 96/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2279197440.0000 - val_loss: 2754231808.0000
Epoch 97/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 2262134016.0000 - val_loss: 2736125440.0000
Epoch 98/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2070664704.0000 - val_loss: 2720456704.0000
Epoch 99/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2286254848.0000 - val_loss: 2729527552.0000
Epoch 100/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1640843264.0000 - val_loss: 2713882368.0000
Epoch 101/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2562958336.0000 - val_loss: 2789159424.0000
Epoch 102/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1706873728.0000 - val_loss: 2723706112.0000
Epoch 103/2000
```

```
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2342678272.0000 - val_loss: 2725446400.0000
Epoch 104/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2366534144.0000 - val_loss: 2722440448.0000
Epoch 105/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1793118464.0000 - val_loss: 2730639104.0000
Epoch 106/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1965067136.0000 - val_loss: 2728505856.0000
Epoch 107/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1954215552.0000 - val_loss: 2713752064.0000
Epoch 108/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2152921856.0000 - val_loss: 2746974208.0000
Epoch 109/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2196276736.0000 - val_loss: 2741342464.0000
Epoch 110/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2148823296.0000 - val_loss: 2728276992.0000
Epoch 111/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2261619456.0000 - val_loss: 2730828032.0000
Epoch 112/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2432824832.0000 - val_loss: 2749893376.0000
Epoch 113/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2705601792.0000 - val_loss: 2712504064.0000
Epoch 114/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2008934144.0000 - val_loss: 2728611840.0000
Epoch 115/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 2052979456.0000 - val_loss: 2728705024.0000
Epoch 116/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2410234624.0000 - val_loss: 2717127680.0000
Epoch 117/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1964448000.0000 - val_loss: 2718841856.0000
Epoch 118/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2070056960.0000 - val_loss: 2729548544.0000
Epoch 119/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2080263936.0000 - val_loss: 2729267456.0000
Epoch 120/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2029256064.0000 - val_loss: 2717577472.0000
Epoch 121/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2156710400.0000 - val_loss: 2715414272.0000
Epoch 122/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1945193600.0000 - val_loss: 2738799104.0000
Epoch 123/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2004746368.0000 - val_loss: 2722514688.0000
```

```
Epoch 124/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2220188928.0000 - val_loss: 2719303168.0000
Epoch 125/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1872482048.0000 - val_loss: 2724576512.0000
Epoch 126/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1729657728.0000 - val_loss: 2739105024.0000
Epoch 127/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2256387840.0000 - val_loss: 2704312064.0000
Epoch 128/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2476898048.0000 - val_loss: 2711046912.0000
Epoch 129/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2034613248.0000 - val_loss: 2721356032.0000
Epoch 130/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 2059774080.0000 - val_loss: 2736240384.0000
Epoch 131/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1821451648.0000 - val_loss: 2717107200.0000
Epoch 132/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2683227136.0000 - val_loss: 2728101632.0000
Epoch 133/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2582176512.0000 - val_loss: 2719382528.0000
Epoch 134/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1999330688.0000 - val_loss: 2704784128.0000
Epoch 135/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2360487680.0000 - val_loss: 2739899648.0000
Epoch 136/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1986506112.0000 - val_loss: 2729891072.0000
Epoch 137/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2012238336.0000 - val_loss: 2719931392.0000
Epoch 138/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2616333824.0000 - val_loss: 2710733056.0000
Epoch 139/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2442691840.0000 - val_loss: 2711245824.0000
Epoch 140/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2310083328.0000 - val_loss: 2721499392.0000
Epoch 141/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1985543936.0000 - val_loss: 2714329600.0000
Epoch 142/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2242437376.0000 - val_loss: 2717502464.0000
Epoch 143/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2747330560.0000 - val_loss: 2703477504.0000
Epoch 144/2000
```

```
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1823108864.0000 - val_loss: 2708506624.0000
Epoch 145/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 2714518528.0000 - val_loss: 2711048192.0000
Epoch 146/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1879564672.0000 - val_loss: 2728506368.0000
Epoch 147/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1826217344.0000 - val_loss: 2719809792.0000
Epoch 148/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2409907200.0000 - val_loss: 2733440768.0000
Epoch 149/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 1914412800.0000 - val_loss: 2725755904.0000
Epoch 150/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2096046592.0000 - val_loss: 2712578304.0000
Epoch 151/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2388133632.0000 - val_loss: 2702692864.0000
Epoch 152/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2112064384.0000 - val_loss: 2721111808.0000
Epoch 153/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2521978880.0000 - val_loss: 2705223168.0000
Epoch 154/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2088065920.0000 - val_loss: 2740433408.0000
Epoch 155/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1712569856.0000 - val_loss: 2705716736.0000
Epoch 156/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2359124224.0000 - val_loss: 2732516608.0000
Epoch 157/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2082784256.0000 - val_loss: 2737767424.0000
Epoch 158/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2487092480.0000 - val_loss: 2714563072.0000
Epoch 159/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 3289060608.0000 - val_loss: 2699545600.0000
Epoch 160/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1731366912.0000 - val_loss: 2707188480.0000
Epoch 161/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2193353472.0000 - val_loss: 2742009856.0000
Epoch 162/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1913428992.0000 - val_loss: 2717517824.0000
Epoch 163/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2237409792.0000 - val_loss: 2719210240.0000
Epoch 164/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2284158976.0000 - val_loss: 2725127168.0000
```

```
Epoch 165/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2172873216.0000 - val_loss: 2722163968.0000
Epoch 166/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 3112625152.0000 - val_loss: 2695592448.0000
Epoch 167/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1788216448.0000 - val_loss: 2714953216.0000
Epoch 168/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1694875264.0000 - val_loss: 2717919744.0000
Epoch 169/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 2484273152.0000 - val_loss: 2699595520.0000
Epoch 170/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2948050176.0000 - val_loss: 2701702400.0000
Epoch 171/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2242286848.0000 - val_loss: 2733200128.0000
Epoch 172/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1973770112.0000 - val_loss: 2717933568.0000
Epoch 173/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1995175552.0000 - val_loss: 2724998656.0000
Epoch 174/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1854029440.0000 - val_loss: 2711711488.0000
Epoch 175/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2149980928.0000 - val_loss: 2719974144.0000
Epoch 176/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1868750080.0000 - val_loss: 2724634112.0000
Epoch 177/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1847371264.0000 - val_loss: 2712119552.0000
Epoch 178/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 2649904128.0000 - val_loss: 2718263552.0000
Epoch 179/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1754343296.0000 - val_loss: 2712455424.0000
Epoch 180/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1980974592.0000 - val_loss: 2714635776.0000
Epoch 181/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2864697088.0000 - val_loss: 2694570496.0000
Epoch 182/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1988237440.0000 - val_loss: 2729396480.0000
Epoch 183/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1964147072.0000 - val_loss: 2724323328.0000
Epoch 184/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2433400832.0000 - val_loss: 2705128448.0000
Epoch 185/2000
```

```
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2446729216.0000 - val_loss: 2706976256.0000
Epoch 186/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 3190483712.0000 - val_loss: 2697138176.0000
Epoch 187/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2625893632.0000 - val_loss: 2697392640.0000
Epoch 188/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2262737152.0000 - val_loss: 2712421376.0000
Epoch 189/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1828110208.0000 - val_loss: 2714019584.0000
Epoch 190/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 1925532160.0000 - val_loss: 2727127552.0000
Epoch 191/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 1932987136.0000 - val_loss: 2705780992.0000
Epoch 192/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2050427008.0000 - val_loss: 2710588928.0000
Epoch 193/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2596121600.0000 - val_loss: 2697830400.0000
Epoch 194/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 3017414912.0000 - val_loss: 2694699776.0000
Epoch 195/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2008515712.0000 - val_loss: 2705484032.0000
Epoch 196/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2293976576.0000 - val_loss: 2758729472.0000
Epoch 197/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1890533376.0000 - val_loss: 2707158784.0000
Epoch 198/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2160132352.0000 - val_loss: 2734403328.0000
Epoch 199/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2128286208.0000 - val_loss: 2710195968.0000
Epoch 200/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 2351901952.0000 - val_loss: 2711869696.0000
Epoch 201/2000
28/28 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 2349799680.0000 - val_loss: 2723586304.0000
```

In [18]:
```
X_test
```

Out[18]:

	OverallQual	GrLivArea	GarageCars	GarageArea	TotalBsmtSF
963	9	1800	2	702	1800
728	5	1776	3	888	1584
97	4	960	1	432	960
723	4	1470	1	548	941
1050	7	1302	2	436	1302
...	...	...	...	...	...
1383	5	1416	2	576	816
842	6	1165	2	490	1127
623	6	1512	2	440	756
437	6	904	1	180	884
225	5	1302	1	280	630

292 rows × 5 columns

In [19]:

```
model.predict(X_test)[:10]
```

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step
```

Out[19]:

```
array([[254187.75 ],
       [259782.08 ],
       [140721.67 ],
       [180050.89 ],
       [177303.42 ],
       [174777.28 ],
       [141315.27 ],
       [208332.28 ],
       [116845.664],
       [105475.43 ]], dtype=float32)
```

In [20]:

```
model.predict(X_test).flatten()[:10]
```

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

Out[20]:

```
array([254187.75 , 259782.08 , 140721.67 , 180050.89 , 177303.42 ,
        174777.28 , 141315.27 , 208332.28 , 116845.664, 105475.43 ],
      dtype=float32)
```

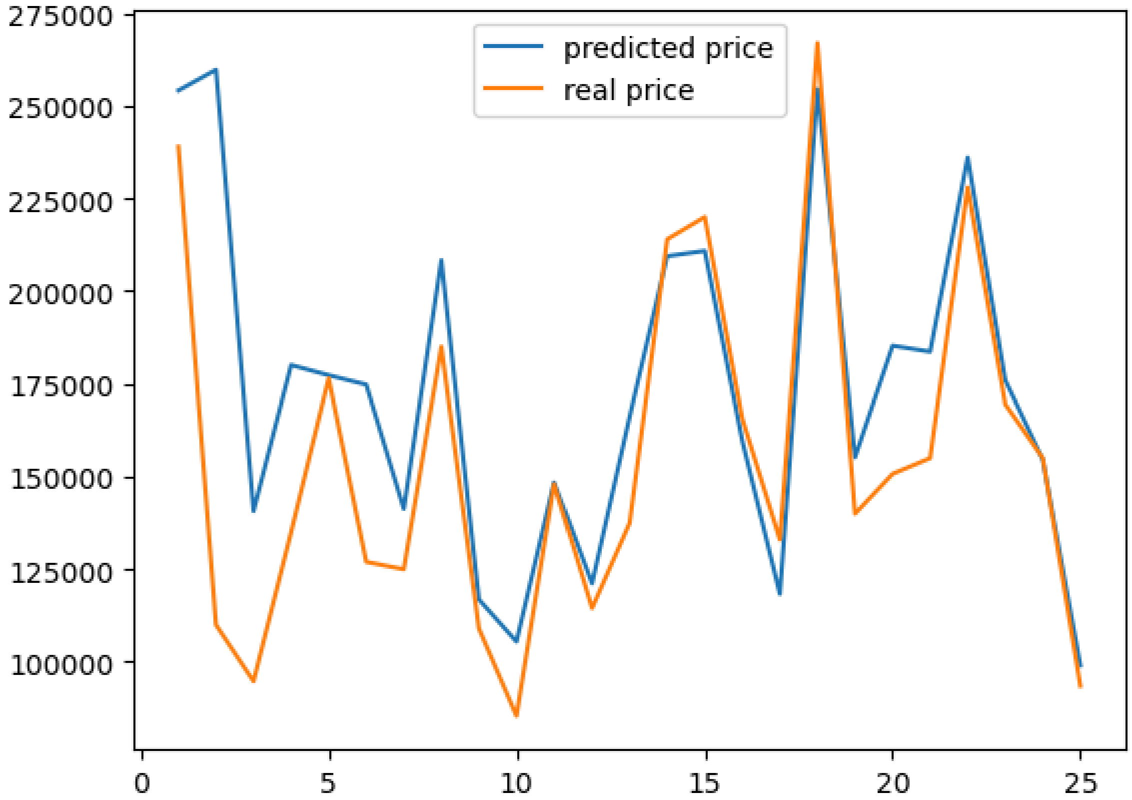
In [21]:

```python
# 예측 값과 실제 값, 실행 번호가 들어갈 빈 리스트를 만듭니다.
real_prices =[]
pred_prices = []
X_num = []

# 25개의 샘플을 뽑아 실제 값, 예측 값을 출력해 봅니다.
n_iter = 0
Y_prediction = model.predict(X_test).flatten()
for i in range(25):
    real = y_test[i]
    prediction = Y_prediction[i]
    print("실제가격: {:.2f}, 예상가격: {:.2f}".format(real, prediction))
    real_prices.append(real)
    pred_prices.append(prediction)
    n_iter = n_iter + 1
    X_num.append(n_iter)
```

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
실제가격: 239000.00, 예상가격: 254187.75
실제가격: 110000.00, 예상가격: 259782.08
실제가격: 94750.00, 예상가격: 140721.67
실제가격: 135000.00, 예상가격: 180050.89
실제가격: 176485.00, 예상가격: 177303.42
실제가격: 127000.00, 예상가격: 174777.28
실제가격: 125000.00, 예상가격: 141315.27
실제가격: 185000.00, 예상가격: 208332.28
실제가격: 109000.00, 예상가격: 116845.66
실제가격: 85400.00, 예상가격: 105475.43
실제가격: 148000.00, 예상가격: 148429.34
실제가격: 114500.00, 예상가격: 121177.91
실제가격: 137500.00, 예상가격: 166152.58
실제가격: 214000.00, 예상가격: 209428.23
실제가격: 220000.00, 예상가격: 210849.05
실제가격: 165600.00, 예상가격: 159605.22
실제가격: 133000.00, 예상가격: 118326.48
실제가격: 267000.00, 예상가격: 254552.92
실제가격: 140000.00, 예상가격: 155204.23
실제가격: 150750.00, 예상가격: 185255.33
실제가격: 155000.00, 예상가격: 183647.23
실제가격: 228000.00, 예상가격: 236091.47
실제가격: 169500.00, 예상가격: 175981.66
실제가격: 155000.00, 예상가격: 154529.52
실제가격: 93500.00, 예상가격: 99036.65
```

In [22]:

```python
# 그래프를 통해 샘플로 뽑은 25개의 값을 비교해 봅니다.

plt.plot(X_num, pred_prices, label='predicted price')
plt.plot(X_num, real_prices, label='real price')
plt.legend()
plt.show()
```


predicted price
real price
275000
250000
225000
200000
175000
150000
125000
100000
0
5
10
15
20
25