House-Price-Prediction Using Machine Learning

Abstract :

Predicting house prices is a crucial task in the real estate industry, offering valuable insights for buyers, sellers, and investors. Machine learning techniques have become a powerful tool for this purpose. This abstract provides an overview of a typical approach to house price prediction using machine learning.

The process begins with data collection, where historical housing prices and relevant property features are gathered. Data preprocessing follows, involving cleaning, encoding , and normalization. Feature selection and engineering help in improving the model's accuracy. The dataset is then divided into training and testing sets, and an appropriate regression algorithm is selected for model training.

Evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean

Squared Error (RMSE) are employed to assess the model's performance. Hyperparameter tuning is conducted to optimize the model, and once satisfactory results are achieved, the model is deployed in a production environment.

Continual monitoring and maintenance are crucial, as house prices can change over time. Ethical considerations and compliance with regulations, if applicable, are essential throughout the process.This abstract highlights the key steps and considerations involved in house price prediction using machine learning, emphasizing the significance of data quality, model selection, and ongoing model management for accurate and reliable predictions in the dynamic real estate market.

Introduction :

The prediction of house prices is a fundamental and practical challenge within the real estate industry. Accurate price estimations are vital for buyers, sellers, and investors to make informed decisions. Traditionally, real estate professionals rely on market knowledge and expertise to gauge property values. However, in the era of big data and advanced technology, machine learning has emerged as a powerful tool for predicting house prices with a high degree of precision.

This introduction sets the stage for the discussion of house price prediction using machine learning. It outlines the significance of the task, the role of data, and the promise of machine learning in providing robust, data-driven insights.

Data Processing :

Data processing is a critical step in the house price prediction using machine learning. It involves several tasks aimed at preparing the raw data for model training and analysis. Here are the key data processing stepss.

Data Collection :

Gather a comprehensive dataset that includes historical house prices and relevant features. Sources may include real estate websites, government records, or data providers.

Data Cleaning :

Address missing values: Identify and handle missing data points in the dataset. Options include imputation, deletion, or using domain-specific knowledge to fill in missing values.

Handle outliers: Detect and manage outliers in the data. Outliers can significantly affect model performance, so you may choose to remove them or transform them.

Feature Selection and Engineering :

Feature selection: Identify and select the most relevant features that are likely to impact house prices. This step reduces dimensionality and enhances model efficiency.

Feature engineering: Create new features that may improve the model's performance. For example, you could calculate the total area of a property by combining the dimensions of its rooms.

Data Transformation :

Categorical data encoding: Convert categorical variables (e.g., property type, location) into a numerical format. Common techniques include one-hot encoding or label encoding. Scaling and normalization: Rescale numerical features to bring them to a common scale (e.g., between 0 and 1) to ensure that no feature dominates others during modeling.

Logarithmic transformation: Apply logarithmic transformations to features with skewed distributions to make them more normally distributed.

Data Splitting :

Divide the preprocessed dataset into training and testing sets. A common split ratio is 80% for training and 20% for testing. This separation ensures that the model is evaluated on unseen data to assess its generalization capability.

Data Visualization (Optional but helpful) :

Create visualizations such as histograms, scatter plots, or correlation matrices to gain insights into the data and relationships between variables. This step can be particularly valuable for understanding feature importance.

Data Quality Check :

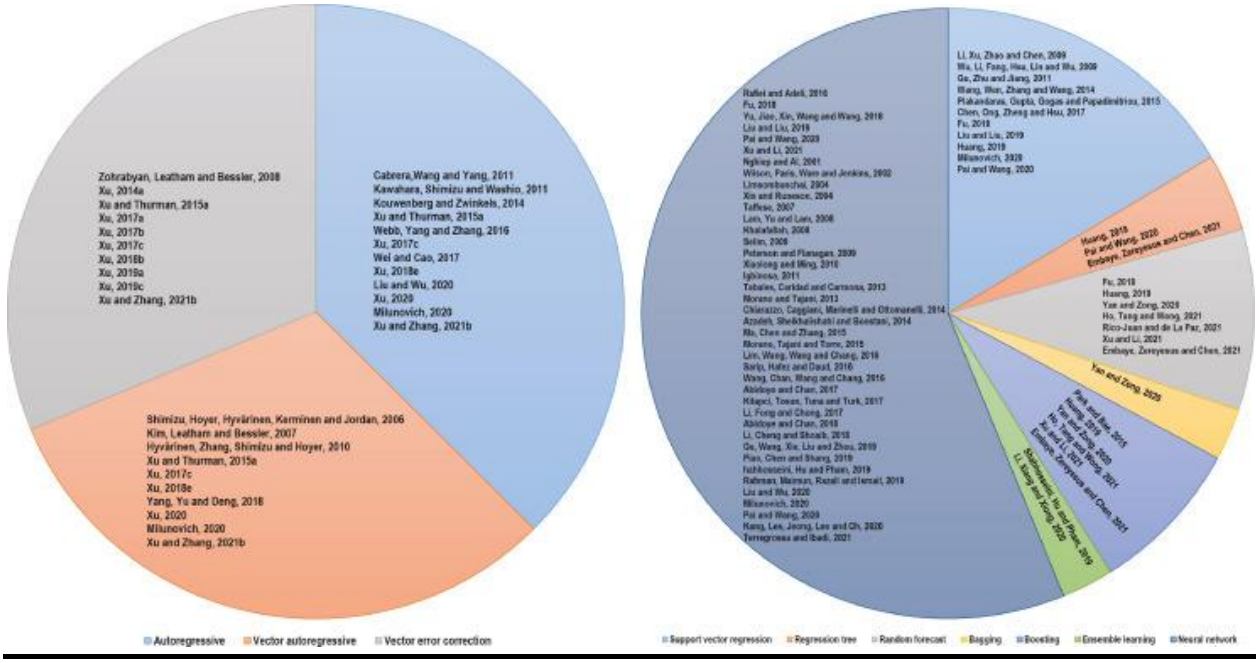
Verify that the preprocessing steps have effectively handled missing values, outliers, and transformed features. Ensure that the data is now in a suitable format for model training.

Save Processed Data :

Save the preprocessed data to a separate file for easy access and reproducibility during model training and testing.

Effective data processing is essential for building an accurate house price prediction model. The quality of the data and the success of these preprocessing steps can significantly impact the model's performance. It is crucial to strike a balance between cleaning and transforming data while preserving valuable information to make informed predictions.

Flow chart :-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Xu, 2014a
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Xu, 2019a
Xu, 2019c
Xu and Zhang, 2021b
Cabrera,Wang and Yang, 2011
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Kouwenberg and Zwinkels, 2014
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Xu, 2017c
Wei and Cao, 2017
Xu, 2018e
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Xu, 2020
Milunovich, 2020
Xu and Zhang, 2021b
Shimizu, Hoyer, Hyvärinen, Kerminen and Jordan, 2006
Kim, Leatham and Bessler, 2007
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Yang, Yu and Deng, 2018
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Autoregressive
Vector autoregressive
Vector error correction
Li, Xu, Zhao and Chen, 2009
Wu, Li, Fang, Hsu, Lin and Wu, 2008
Ge, Zhu and Jiang, 2011
Wang, Wan, Zhang and Wang, 2014
Plakandaras, Gupta, Gogas and Papadimitriou, 2015
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Shahwan, Xu and Zhang, 2019
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Rafiei and Adeli, 2016
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Yu, Jiao, Xin, Wang and Wang, 2018
Liu and Liu, 2019
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Nghiep and Al, 2001
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Taffese, 2007
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Xiaolong and Ming, 2010
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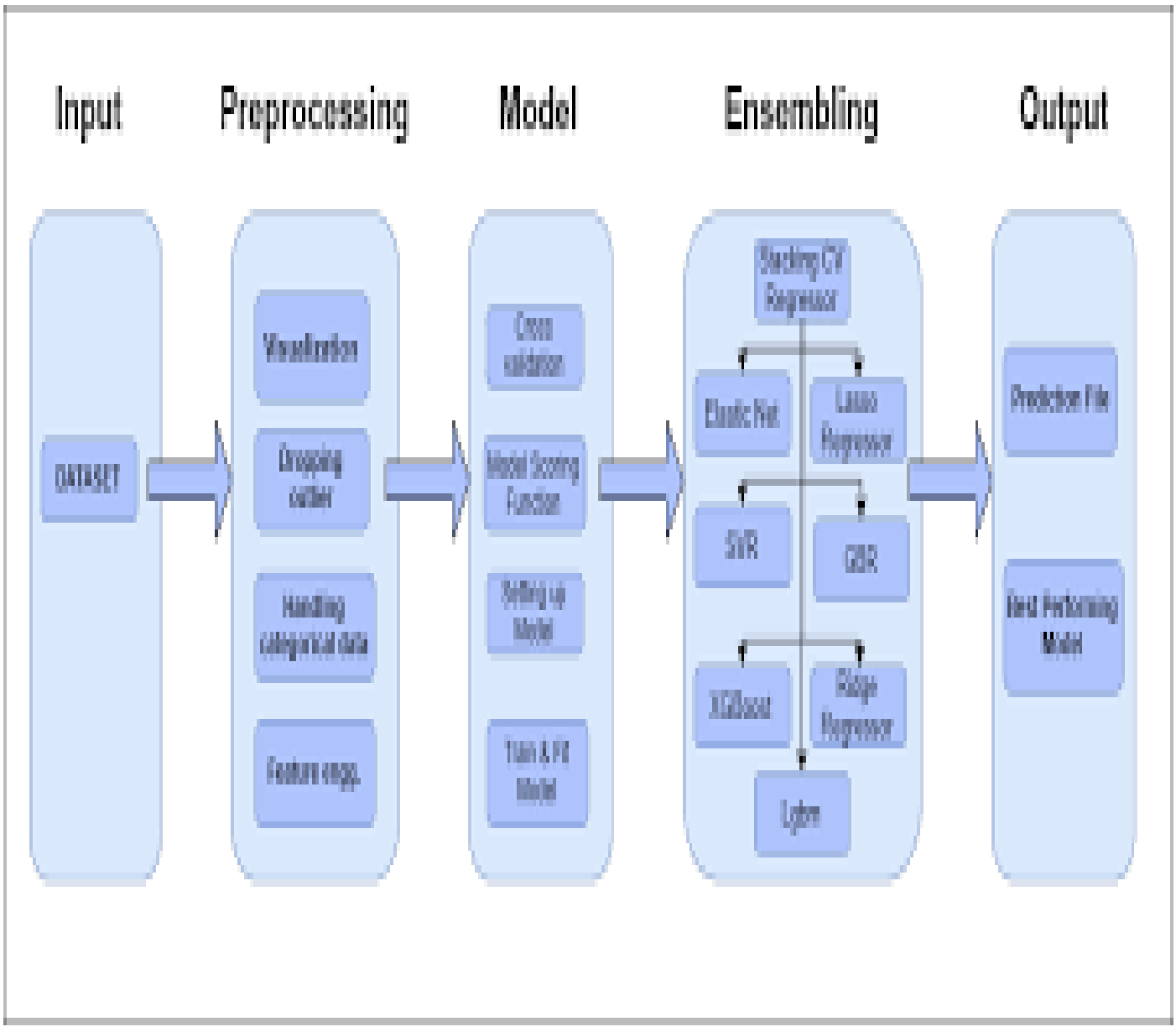
Tebales, Caridad and Carnoso, 2013
Moreno and Tejani, 2013
Chiarazzo, Caggiani, Marinelli and Ottomanelli, 2014
Azadeh, Sheikhalishahi and Boostan, 2014
Ma, Chen and Zhang, 2015
Moreno, Tejani and Torre, 2015
Lim, Wang, Wang and Chung, 2016
Ranjo, Hafez and Daud, 2016
Wang, Chan, Wang and Chang, 2016
Abidoye and Chan, 2017
Kitapci, Tosun, Tuna and Turk, 2017
Li, Fong and Chong, 2017
Abidoye and Chan, 2018
Li, Cheng and Shoaib, 2018
Ge, Wang, Xie, Liu and Zhou, 2019
Phan, Chen and Shang, 2019
Ishikawajima, Ha and Pfaan, 2019
Rahman, Mannan, Kaisti and Ismail, 2019
Liu and Wu, 2020
Milunovich, 2020
Pai and Wang, 2020
Kang, Lee, Jeong, Lee and Oh, 2020
Terregrossa and Ibadi, 2021
Support vector regression
Regression tree
Random forecast
Bagging
Boosting
Ensemble learning
Neural network


Executing the acquisitions
Identification of target market and properties
Building the plan
Evaluate resources


Input
Preprocessing
Model
Ensembling
Output
DATASET
Visualization
Dropping outlier
Handling categorical data
Feature engg.
Cross validation
Model Scoring Function
Shifting up Model
Train & Fit Model
Stacking CV Regressor
Elastic Net
Lasso Regressor
SVR
GBR
XGBoost
Ridge Regressor
Lgbm
Prediction File
Best Performing Model

PROGRAM:-

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

In [2]:
df=pd.read_csv("/kaggle/input/usa-
housing/USA_Housing.csv")
veri = df.copy()
veri.head()

Out[2]:
```

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.458574	5.682861	7.009188	4.09	23086.800503	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.642	6.0029	6.7308	3.0	40173.072	1.505891e	188 Johnson Views

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
	455	00	21	9	174	+06	Suite 079\nLake Kathleen, CA...
2	61287.067179	5.865890	8.512727	5.13	36882.159400	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
							06482...
3	63345.240046	7.188236	5.586729	3.26	34310.242831	1.260617e+06	USS Barnett\nFPO AP 44820

	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
4	59982.197226	5.040555	7.839388	4.23	26354.109472	6.309435e+05	USNS Raymond\nFPO AE 09386

In [3]:

```
veri.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column                        Non-Null Count
Dtype
```

```
---  ------                          --------------  --
---
 0   Avg. Area Income                5000 non-null
float64
 1   Avg. Area House Age             5000 non-null
float64
 2   Avg. Area Number of Rooms       5000 non-null
float64
 3   Avg. Area Number of Bedrooms    5000 non-null
float64
 4   Area Population                 5000 non-null
float64
 5   Price                           5000 non-null
float64
 6   Address                         5000 non-null
object
dtypes: float64(6), object(1)
memory usage: 273.6+ KB
```

In [4]:

```
veri= veri.drop(columns="Address",axis=1)
```

In [5]:

```
df.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
Avg. Area Income	5000.0	6.858311e+04	10657.991214	17796.631190	61480.562388	6.880429e+04	7.578334e+04	1.077017e+05
Avg. Area House Age	5000.0	5.977222e+00	0.991456	2.644304	5.322283	5.970429e+00	6.650808e+00	9.519088e+00

	count	mean	std	min	25%	50%	75%	max
Avg. Area Number of Rooms	5000.0	6.987792e+00	1.005833	3.236194	6.299250	7.002902e+00	7.665871e+00	1.075959e+01
Avg. Area Num	5000.	3.981330e+00	1.234137	2.000000	3.140000	4.050000e+00	4.490000e+00	6.500000e+00

	count	mean	std	min	25%	50%	75%	max
ber of Bedrooms	0							
Area Population	50000.0	3.616352e+04	9925.650114	172.610686	29403.928702	3.619941e+04	4.286129e+04	6.962171e+04
Pri	5	1.2	353	159	997	1.2	1.4	2.4

	count	mean	std	min	25%	50%	75%	max
ce	0000.00	32073e+06	117.626581	38.657923	577.135049	32669e+06	71210e+06	69066e+06

In [6]:
```
sns.pairplot(veri)
```

```
/opt/conda/lib/python3.10/site-
packages/seaborn/axisgrid.py:118: UserWarning: The
figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[6]:
```
<seaborn.axisgrid.PairGrid at 0x7819c8fe0d90>
```

In [7]:
```
sns.heatmap(veri.corr(),annot=True)
```

Out[7]:
```
<Axes: >
```

In [8]:

```
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import
variance_inflation_factor

y = veri["Price"]
X= veri.drop(columns="Price",axis=1)

cons = sm.add_constant(X)
vif= pd.DataFrame()
vif["variables"]=X.columns
vif["vif"]=[variance_inflation_factor(cons,i+1) for i
in range(X.shape[1])]
vif
```

Out[8]:

	variables	vif
0	Avg. Area Income	1.001159

	variables	vif
1	Avg. Area House Age	1.000577
2	Avg. Area Number of Rooms	1.273535
3	Avg. Area Number of Bedrooms	1.274413
4	Area Population	1.001266

In [9]:

```
from sklearn.model_selection import
train_test_split,cross_val_score
```

```
X_train, X_test, y_train, y_test =
train_test_split(X, y,

test_size=0.2,

random_state=42)
```

In [10]:

```
from sklearn.preprocessing import StandardScaler

ss = StandardScaler()

X_train = ss.fit_transform(X_train)
X_test = ss.transform(X_test)
```

In [11]:

```
import sklearn.metrics as mt

def cross_val(model):
    vali=cross_val_score(model,X,y,cv=10)
    return vali.mean()
def success(true_,pred):
    rmse=mt.mean_absolute_error(true_,pred)
    r2=mt.r2_score(true_,pred)
    return[rmse,r2]
```

In [12]:

```
from sklearn.linear_model import
LinearRegression,Ridge,Lasso,ElasticNet
li_model=LinearRegression()
li_model.fit(X_train,y_train)
li_pred = li_model.predict(X_test)
```

```
ridge_model=Ridge(alpha=0.1)
ridge_model.fit(X_train,y_train)
ridge_pred = ridge_model.predict(X_test)

lasso_model=Lasso(alpha=0.1)
lasso_model.fit(X_train,y_train)
lasso_pred = lasso_model.predict(X_test)


elas_model=ElasticNet(alpha=0.1)
elas_model.fit(X_train,y_train)
elas_pred = elas_model.predict(X_test)


In [13]:
result=[["Linear
model",success(y_test,li_pred)[0],success(y_test,li_p
red)[1],cross_val(li_model)],
        ["Ridge
model",success(y_test,ridge_pred)[0],success(y_test,r
idge_pred)[1],cross_val(ridge_model)],
        ["Lasso
model",success(y_test,lasso_pred)[0],success(y_test,l
asso_pred)[1],cross_val(lasso_model)],
        ["ElasticNet
model",success(y_test,elas_pred)[0],success(y_test,el
as_pred)[1],cross_val(elas_model)]
        ]
pd.options.display.float_format="{:.4f}".format
result=pd.DataFrame(result,columns=["Model","RMSE","R
2","Verification"])
result


Out[13]:
```

	Model	RMSE	R2	Verification
0	Linear model	80879.0972	0.9180	0.9174
1	Ridge model	80878.9638	0.9180	0.9174
2	Lasso model	80879.0910	0.9180	0.9174
3	ElasticNet model	81617.9048	0.9157	0.9165