HOUSING: PRICE PREDICTION

Submitted by:

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ACKNOWLEDGMENT

Data Sources:- The dataset provided as train.csv & test.csv, Data Description.txt

The learning, practice and evaluation projects and the study material provided at DataTrained Academy as well as Flip Robo Technologies have helped in successful completion of the project

INTRODUCTION

• Business Problem Framing

A US-Based housing company named Surprise Housing has decided to enter the Australian Market. It is looking at prospective properties to buy houses to enter the market.

Build a Model using Machine Learning in order to predict the actual value of the prospective properties and decide whether to invest in them or not.

Houses are one of the necessary needs of each and every person around the globe, Data science comes as a very important tool to solve problems in the domain to help the companies increase their overall revenue, profits, improving their marketing strategies and focusing on changing trends in house sales and purchases.

• Conceptual Background of the Domain Problem

The domain related concepts that will be useful for better understanding of the project would be:- Sales, Statistical Analysis, Data Analysis, Machine Learning.

• Motivation for the Problem Undertaken

The objective behind the project is to model the price of houses with the available independent variables. This model will then be used by the management to understand how exactly the prices vary with the variables. They can accordingly manipulate the strategy of the firm and concentrate on areas that will yield high returns. Further, the model will be a good way for the management to understand the pricing dynamics of a new market.

Analytical Problem Framing

- **Mathematical/ Analytical Modeling of the Problem**
  1. Dataset Analysis :-
     a. Dividing the dataset's variables in 4 data types:-
        i. Categorical (Nominal)
        ii. Categorical (Ordinal)
        iii. Numerical (Discrete)
        iv. Numerical (Continuous)
     b. Noting down each column's Null Values, Value Counts and understanding each feature's Distribution.
     c. From the above initial analysis, deciding the unimportant features to be dropped.

(A)Dividing the dataset's variables in 4 data types

i. NOMINAL VARIABLES

Feature	Type	Type	Null Value	Maximum Occurance (%	Second Most Occuring (%)
MSSubClass	Categorical	Nominal	0.00%	20 (37%)	60 (21%)
MSZoning	Categorical	Nominal	0.00%	RL (80%)	RM (14%)
Street	Categorical	Nominal	0.00%	Pave (99.70%)	-
Alley	Categorical	Nominal	93.50%	Grvl (3.50%)	Pave (3.10%)
Utilities	Categorical	Nominal	0.00%	AllPub (100%)	-
LotConfig	Categorical	Nominal	0.00%	Inside (72%)	Corner (19%)
Neighborhood	Categorical	Nominal	0.00%	NAMes (16%)	CollgCr (10%)
Condition1	Categorical	Nominal	0.00%	Norm (86%)	-
Condition2	Categorical	Nominal	0.00%	Norm (99%)	-
RoofMat1	Categorical	Nominal	0.00%	CompShg(98%)	-
RoofStyle	Categorical	Nominal	0.00%	Gable(78%)	Hip(19%)
Exterior1st	Categorical	Nominal	0.00%	VinylSd(34%)	HdBoard(15%)
Exterior2nd	Categorical	Nominal	0.00%	VinylSd(33%)	MetalSd(15%)
MasVnrType	Categorical	Nominal	0.60%	None (60%)	BrkFace(30%)
Foundation	Categorical	Nominal	0.00%	Cblock(44%)	Pconc(44%)
Heating	Categorical	Nominal	0.00%	GasA(98%)	-
CentralAir	Categorical	Nominal	0.00%	Y(93.30%)	
Electrical	Categorical	Nominal	0.00%	SBrkr(91.61%)	
GarageType	Categorical	Nominal	5.50%	Attchd(59%)	Detchd(27%)
SaleType	Categorical	Nominal	0.00%	WD(85.5%)	-
SaleCondition	Categorical	Nominal	0.00%	Normal(81%)	-

(A)Dividing the dataset's variables in 4 data types

ii. ORDINAL VARIABLES

Feature	Type	Type	Null Value	Maximum Occurance (%	Second Most Occuring (%)
BldgType	Categorical	Ordinal	0.00%	1Fam (83%)	-
LotShape	Categorical	Ordinal	0.00%	Reg (64%)	-
LandContour	Categorical	Ordinal	0.00%	Lvl (90%)	-
LandSlope	Categorical	Ordinal	0.00%	Gtl (95%)	-
HouseStyle	Categorical	Ordinal	0.00%	1story (49.50%)	2story (31%)
OverallQual	Categorical	Ordinal	0.00%	5 (27%)	6 (25%)
OverallCond	Categorical	Ordinal	0.00%	5 (55%)	6 (18%)
ExterQual	Categorical	Ordinal	0.00%	TA(61%)	Gd(34%)
ExterCond	Categorical	Ordinal	0.00%	TA(88%)	Gd(10%)
BsmtQual	Categorical	Ordinal	2.60%	TA(44%)	Gd(43%)
BsmtCond	Categorical	Ordinal	2.60%	TA(89%)	-
BsmtExposure	Categorical	Ordinal	2.60%	No(65%)	-
BsmtFinType1	Categorical	Ordinal	2.60%	Unf(29.50%)	GLQ(28.30%)
BsmtFinType2	Categorical	Ordinal	2.60%	Unf(86%)	-
HeatingQC	Categorical	Ordinal	0.00%	Ex(50%)	TA(30%)
KitchenQual	Categorical	Ordinal	0.00%	TA(50%)	Gd(41%)
Functional	Categorical	Ordinal	0.00%	Typ(93%)	
FireplaceQu	Categorical	Ordinal	47%	Gd(26%)	TA(22%)
GarageFinish	Categorical	Ordinal	5.50%	Unf(42%)	RFn(29%)
GarageQual	Categorical	Ordinal	5.50%	TA(90%)	-
GarageCond	Categorical	Ordinal	5.50%	TA(91%)	-
PavedDrive	Categorical	Ordinal	0.00%	Y(92%)	-
PoolQC	Categorical	Ordinal	99.40%	-	-
Fence	Categorical	Ordinal	80%	-	-
MiscFeature	Categorical	Ordinal	96.25%	-	-

(A)Dividing the dataset's variables in 4 data types

iii.DISCRETE VARIABLES

Feature	Type	Type	Null Value	Maximum Occurance (%)	Second Most Occuring (%)	Range
YearBuilt	Numerical	Discrete	0.00%	2006 (5%)	2005 (4.5%)	1875-2010
GarageYrBlt	Numerical	Discrete	5.50%	2006(4.50%)	2005(4.50%	1900-2010
YearRemodAdd	Numerical	Discrete	0.00%	1950(12.50%	2006(7.00%	1950-2010
TotRmsAbvGrd	Numerical	Discrete	0.00%	6(28%)	7(23%)	2-4
BsmtFullBath	Numerical	Discrete	0.00%	0(59%)	1(40%)	0-3
BsmtHalfBath	Numerical	Discrete	0.00%	0(94.60%)		0-2
FullBath	Numerical	Discrete	0.00%	2(52%)	1(45%)	0-3
HalfBath	Numerical	Discrete	0.00%	0(62%)	1(37%)	0-2
BedroomAbvGr	Numerical	Discrete	0.00%	3(55%)	2(24%)	0-8
KitchenAbvGr	Numerical	Discrete	0.00%	1(95.40%)	-	0-3
Fireplaces	Numerical	Discrete	0.00%	0(47%)	1(44%)	0-3
GarageCars	Numerical	Discrete	0.00%	2(57%)	1(25%)	0-4
MiscVal	Numerical	Discrete	0.00%	0(96.40%)	-	-
MoSold	Numerical	Discrete	0.00%	6(17.4%)	7(16%)	1-12
YrSold	Numerical	Discrete	0.00%	2007(22.6%)	2009(22.3%	2006-2010

(A)Dividing the dataset's variables in 4 data types

iv. CONTINUOUS VARIABLES

Feature	Type	Type	Null Value	Maximum Occurance (%)	Second Most Occuring (%)	Majority Range	Skewed	Skew Range	Range
Id	Numerical	Continous	0.00%	-	-	-	-	-	-
LotFrontage	Numerical	Continous	18.30%	60 (10%)	-	60-80	Right	132-313	21.0 - 313.0
LotArea	Numerical	Continous	0.00%	9600 (2%)	-	7800-11100	Right	20900-164660	1300-164660
MasVnrArea	Numerical	Continous	0.60%	0.0(60%)	-	-	Right	416-1600	0-1600
BsmtFinSF1	Numerical	Continous	0.00%	0(32%)	-	-	Right	1016-5644	0-5644
BsmtFinSF2	Numerical	Continous	0.00%	0(88.4%)	-	-	Right	30-1474	0-1474
BsmtUnfSF	Numerical	Continous	0.00%	0(8.30%)	-	-	Right	1500-2336	0-2336
TotalBsmtSF	Numerical	Continous	0.00%	0(2.6%)	864(2.4%)	-	Right	2400-6110	0-6110
1stFlrSF	Numerical	Continous	0.00%	864(1.6%)	1040(1.1%)	-	Right	2300-4692	334-4692
2ndFlrSF	Numerical	Continous	0.00%	0(57%)	-	-	Right	1200-2065	0-2065
LowQualFinSF	Numerical	Continous	0.00%	0(98%)	-	-	-	-	-
GrLivArea	Numerical	Continous	0.00%	864 (1.4%)	1040 (0.95%	-	Right	3100-5642	334-5642
GarageArea	Numerical	Continous	0.00%	0(5.5%)	440(3.8%)	-	Right	900-1418	0-1418
WoodDeckSF	Numerical	Continous	0.00%	0(52%)	-	-	Right	300-857	0-857
OpenPorchSF	Numerical	Continous	0.00%	0(45.50%)	-	-	Right	180-547	0-547
EnclosedPorch	Numerical	Continous	0.00%	0(85.50%)	-	-	-	-	0-552
3SsnPorch	Numerical	Continous	0.00%	0(98%)	-	-	-	-	0-508
ScreenPorch	Numerical	Continous	0.00%	0(92%)	-	-	-	-	0-480
PoolArea	Numerical	Continous	0.00%	0(99.40%)	-	-	-	-	0-738
SalePrice	Numerical	Continous	0.00%	-	-	-	-	-	34900-755000

(B)Noting down each column's Null Values, Value Counts and understanding each feature's Distribution.

(C)From the above initial analysis, deciding the unimportant features to be dropped.

OBSERVATIONS :-

1) Id
Numerical Variable
This is just a pointer variable and not useful in predictive analysis.
Hence, WE SHALL DROP THIS COLUMN

2) MSSubClass
Categorical Variable
Identifies the type of dwelling involved in the sale.
Has no null values
Maximum Occurances :-
20 (1-STORY 1946 & NEWER ALL STYLES) 37%
60 (2-STORY 1946 & NEWER) 21%
50 (1-1/2 STORY FINISHED ALL AGES) 10%

Majority Dwelling = 1-story & 2-story 1946 & NEWER

3) MSZoning
Categorical Variable
Identifies the general zoning classification of the sale.
No Null Values
Maximum Occurances :-
RL (Residential Low Density) 80%
RM (Residential Medium Density) 14%
Majority Zoning = Residential Low Density Zone

4) LotFrontage
Continous Variable
Linear feet of street connected to property
No Null Values
Maximum Occurance = 60.0 (10%)
Majority Street Size = 60 to 80 feet
Right skewed values = 132-313 feet

5) LotArea
Continous Variable
Lot size in square feet
No Null Values
Maximum Occurance = 9600 (2%)
Majority Lot Size = 7800 to 11100 square feet

Right Skewed Values = 20900 to 164660 sq feet

6) Street
Categorical Variable
Type of road access to property
No Null Values
Maximum Occurance = Pave (Paved) (99.7%)
Almost all the roads are paved

7) Alley
Categorical Variable
Type of alley access to property
Null Values = 1091 (93.50%)
Grvl = 41 (3.5%)
Pave = 36 (3.1%)

Since the imputation of values to be done is 93.50%
It is better to drop this column than imputing 93.50% of aritifical values.
Hence, WE SHALL DROP THIS COLUMN

8) LotShape
Categorical Variable
General shape of property
No Null Values
Maximum Occurance = Reg (Regular) (64%)
Majority Shape = Regular & Slightly Irregular

9) LandContour
Categorical Variable
Flatness of the property
No Null Values
Maximum Occurance = Lvl (Near Flat/Level) (90%)
Most of the properties are Near Flat/Level

10) Utilities
Categorical Variable
Type of utilities available
No Null Values
Maximum Occurance = AllPub (All public Utilities (E,G,W,& S)) 100%
Since all the properites have all the public utilities available
It will make no difference in the predictive analysis.
Hence, WE SHALL DROP THIS COLUMN

11) LotConfig
Categorical Variable
Lot configuration
No Null Values
Maximum Occurance =
Inside (Inside lot) (72%)
Corner (Corner lot) (19%)
Most of the properties are Inside or Corner Lot

12) LandSlope
Categorical Variable
Slope of property
No Null Values
Maximum Occurance = Gtl (Gentle slope) (95%)
Almost all the properites have a gentle slope

13) Neighborhood
Categorical Variable
Physical locations within Ames city limits
No Null Values
Maximum Occurance =
NAmes (North Ames) (16%)
CollgCr (College Creek) (10%)

14) Condition1
Categorical Variable
Proximity to various conditions
No Null Values
Maximum Occurance = Norm (Normal) (86%)
Most of the properites has a normal proximity

15) Condition2
Categorical Variable
Proximity to various conditions (if more than one is present)
No Null Values
Maximum Occurance = Norm (Normal) (99%)
Almost all the properites have a normal proximity (secondary)

16) BidgType
Categorical Variable
Type of dwelling
No Null Values
Maximum Occurance = 1Fam (Single-family Detached) (83%)
Most of the properites has a single family detached dwelling

17) HouseStyle
Categorical Variable
Style of dwelling
No Null Values
Maximum Occurance =
1story (One story) (49.50%)
2Story (Two story) (31.00%)
Most of the properties have One & Two Stories

18) OverallQual
Categorical Variable (Ordinal)
Rates the overall material and finish of the house
No Null Values
Maximum Occurance =

5 (Average) (27%)
6 (Above Average) (25%)
Majority Material Quality = 4 to 8

19) OverallCond
Categorical Variable (Ordinal)
Rates the overall condition of the house
No Null values
Maximum Occurance =
5 (Average) (55%)
6 (Above Average) (18%)
7 (Good) (15%)
Majority Condition Quality = 5 to 7

20) YearBuilt
Continous Variable (Discrete)
Original construction date
No Null values
Maximum Occurance =
2006 (5%)
2005 (4.50%)
2007 (3.50%)
2004 (3.20%)
2003 (2.80%)
Majority Construction Range = 2002 to 2007

21) YearRemodAdd
Continous Variable (Discrete)
Remodel date (same as construction date if no remodeling or additions)
No Null values
Maximum Occurance =
1950 (12.50%)
2006 (7.00%)
2007 (5.50%)
2005 (5.00%)
2004 (4.00%)
Majority Remodel Range = 1950 & 2004-2007

22) RoofStyle
Categorical Variable
Type of roof
No Null Values
Maximum Occurance =
Gable (78%)
Hip (19%)
Almost all the properties have Gable & Hip roof

23) RoofMat1
Categorical Variable
Roof material
No Null Values

Maximum Occurance = CompShg (Standard (Composite) Shingle) (98%)
Almost all the properites have standard Roof Material

24) Exterior1st
Categorical Variable
Exterior covering on house
No Null Values
Maximum Occurance =
VinylSd (Vinyl Siding)(34%)
HdBoard (Hard Board)(15%)
MetalSd (Metal Siding)(15%)
Wd Sdng (Wood Siding) (15%)
Plywood (Plywood) (8%)

25) Exterior2nd
Categorical Variable
Exterior covering on house (if more than one material)
No Null Values
Maximum Occurance =
VinylSd (Vinyl Siding)(33%)
MetalSd (Metal Siding)(15%)
HdBoard (Hard Board)(14.50%)
Wd Sdng (Wood Siding) (14%)
Plywood (Plywood) (10%)

26) MasVnrType
Categorical Variable
Masonry veneer type
Null Values = 7 (0.6%)
Maximum Occurance =
None (None) (60%)
BrkFace (Brick Face) (30%)

27) MasVnrArea
Continous Variable
Masonry veneer area in square feet
Null Values = 7 (0.6%)
Maximum Occurance = 0.0 (60%)
Right Skewed Range = 416 to 1600
Since, the veneer type is none in 60% properites
the area of veneer in 60% properites is 0

28) ExterQual
Categorical Variable (Ordinal)
Evaluates the quality of the material on the exterior
No Null Values
Maximum Occurance =
TA Average/Typical (61%)
Gd Good (34%)
Most of the properites have good or average quality exterior

29) ExterCond
Categorical Variable (Ordinal)
Evaluates the present condition of the material on the exterior
No Null Values
Maximum Occurance =
TA Average/Typical (88%)
Gd Good (10%)
Majority of the properites have average quality exterior

30) Foundation
Categorical Variable
Type of foundation
No Null Values
Maximum Occurances =
CBlock Cinder Block (44%)
PConc Poured Contrete (44%)
Majority of the properites have CBlock/PConc Foundation

31) BsmtQual
Categorical Variable (Ordinal)
Evaluates the height of the basement
Null Values = 30 (2.6%)
Maximum Occurance =
TA Typical (80-89 inches) (44%)
Gd Good (90-99 inches) (43%)
Height of basement of majority of the houses is 80-99 inches

32) BsmtCond
Categorical Variable (Ordinal)
Evaluates the general condition of the basement
Null Values = 30 (2.6%)
Maximum Occurance =
TA Typical - slight dampness allowed (89%)
Majority of the houses have a typical quality basement

33) BsmtExposure
Categorical Variable
Refers to walkout or garden level walls
Null Values = 31 (2.6%)
Maximum Occurance = No (No Exposure) (65%)
Majority of houses have No Exposure to walkout

34) BsmtFinType1
Categorical Variable (Ordinal)
Rating of basement finished area
NUll Values = 30 (2.6%)
Maximum Occurances =
Unf (Unfinshed) (29.50%)
GLQ (Good Living Quarters) (28.30%)

35) BsmtFinSF1

Continous Variable
Type 1 finished square feet
No Null values
Maximum Occurance = 0 (32%)
Right Skewed Range = 1016 to 5644
Left Skewed at 0

36) BsmtFinType2
Categorical Variable (Ordinal)
Rating of basement finished area (if multiple types)
Null Values = 31 (2.6%)
Maximum Occurance = Unf (Unfinshed) (86%)

37) BsmtFinSF2
Continous Variable
Type 2 finished square feet
No NUll values
Maximum Occurance = 0 (88.4%)
Right Skewed Range = 30 to 1474

38) BsmtUnfSF
Continous Variable
Unfinished square feet of basement area
No NULL Values
Maximum Occurance = 0 (8.30%)
Right Skewed Range = 1500 to 2336

39) TotalBsmtSF
Continous Variable
Total square feet of basement area
No NULL Values
Maximum Occurances=
0 (2.6%)
864 (2.4%)
Left Skewed at 0
Right Skewed Range = 2400 to 6110

40) Heating
Categorical Variable
Type of heating
No NULL Values
Maximum Occurance = GasA (Gas forced warm air furnace) (98%)
Almost all the houses have GasA heating type

41) HeatingQC
Categorical Variable (Ordinal)
Heating quality and condition
No NULL Values
Maximum Occurances=
Ex (Excellent) (50%)
TA (Average/Typical) (30%)

Half of the houses have excellent and 30% average heating quality

42) CentralAir
Categorical Variable
Central air conditioning
No NULL Values
Maximum Occurance = Y (Yes) (93.3%)
Almost all the houses have central ac

43) Electrical
Categorical Variable
Electrical system
No NULL Values
Maximum Occurance = SBrkr (Standard Circuit Breakers & Romex) (91.61%)
Almost all the houses have Standard circuit electrical system

44) 1stFlrSF
Countinous Variable
First Floor square feet
No NULL Values
Maximum Occurances =
864 (1.6%)
1040 (1.1%)
912 (1.1%)
894 (1%)
Right Skewed Range = 2300 to 4692

45) 2ndFlrSF
Countinous Variable
Second Floor square feet
No NULL Values
Maximum Occurances = 0 (57%)
Left skewed at 0
Right skewed range = 1200 to 2065
More than 56% houses do not have a second floor

46) LowQualFinSF
Countinous Variable
Low quality finished square feet (all floors)
No NULL Values
Maximum Occurances = 0 (98%)
only 2% houses have low quality finish

47) GrLivArea
Countinous Variable
Above grade (ground) living area square feet
No NULL Values
Maximum Occurances =
864 (1.4%)
1040 (0.95%)
894 (0.86%)

Right Skewed Range = 3100 to 5642

48) BsmtFullBath
Numerical Variable (discrete)
Basement full bathrooms
No NULL Values
Maximum Occurances =
0 (59%)
1 (40%)

49) BsmtHalfBath
Numerical Variable (discrete)
Basement half bathrooms
No NULL Values
Maximum Occurance = 0 (94.60%)

50) FullBath
Numerical Variable (discrete)
Full bathrooms above grade
No NULL Values
Maximum Occurances =
2 (52%)
1 (45%)

51) HalfBath
Numerical Variable (discrete)
Half baths above grade
No NULL Values
Maximum Occurances =
0 (62%)
1 (37%)

52) BedroomAbvGr
Numerical Variable (discrete)
Bedrooms above grade (does NOT include basement bedrooms)
No NULL Values
Maximum Occurances =
3 (55%)
2 (24%)
4 (15%)

53) KitchenAbvGr
Numerical Variable (discrete)
Kitchens above grade
No NULL Values
Maximum Occurance = 1 (95.40%)

54) KitchenQual
Categorical variable (Ordinal)
Kitchen quality
No NULL Values

Maximum Occurances =
TA (Typical/Average) (50%)
Gd (Good) (41%)

55) TotRmsAbvGrd
Numerical Variable (Discrete)
Total rooms above grade (does not include bathrooms)
No NULL Values
Maximum Occurances=
6 (28%)
7 (23%)
5 (19%)
8 (13%)

56) Functional
Categorical Variable (Ordinal)
Home functionality (Assume typical unless deductions are warranted)
No NULL Values
Maximum Occurance = Typ (Typical Functionality) (93%)

57) Fireplaces
Numerical Variable (Discrete)
Number of fireplaces
No NULL Values
Maximum Occurances=
0 (47%)
1 (44%)

58) FireplaceQu
Categorical Variable (Ordinal)
Fireplace quality
Null Values = 551 (47%)
Maximum Occurances=
Gd (Good - Masonry Fireplace in main level) (26%)
TA (Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement) (22%)

59) GarageType
Categorical Variable
Garage location
Null Values = 64 (5.5%)
Maximum Occurances=
Attchd (Attached to home) (59%)
Detchd (Detached from home) (27%)

60) GarageYrBlt
Numerical Variable (Discrete)
Year garage was built
Null Values = 64 (5.5%)
Maximum Occurances=
2006 (4.50%)
2005 (4.50%)

2007 (3.50%)
2003 (3.20%)
2004 (3.10%)
Maximum Range = 2001 to 2008

61) GarageFinish
Categorical Variable
Interior finish of the garage
Null Values = 64 (5.5%)
Maximum Occurances =
Unf (Unfinished) (42%)
RFn (Rough Finished) (29%)
Fin (Finished) (24%)

62) GarageCars
Numerical Variable (Discrete)
Size of garage in car capacity
No NULL Values
Maximum Occurances =
2 (57%)
1 (25%)
6 (13%)

63) GarageArea
Continous Variable
Size of garage in square feet
No NULL Values
Maximum Occurances =
0 (5.5%)
440 (3.8%)
576 (3.4%)
240 (2.7%)
528 (2.3%)
Left Skewed at 0
Right Skewed Range = 900 to 1418

64) GarageQual
Categorical Variable (Ordinal)
Garage quality
Null Values = 64 (5.5%)
Maximum Occurance = TA (Typical/Average) (90%)

65) GarageCond
Categorical Variable (Ordinal)
Garage condition
Null Values = 64 (5.5%)
Maximum Occurance = TA (Typical/Average) (91%)

66) PavedDrive
Categorical Variable (Ordinal)
Paved driveway

No NULL Values
Maximum Occurance= Y (Paved) (92%)

67) WoodDeckSF
Continous Variable
Wood deck area in square feet
No NULL Values
Maximum Occurance = 0 (52%)
Left Skewed at 0
Right Skewed Range = 300 to 857

68) OpenPorchSF
Continous Variable
Open porch area in square feet
No NULL Values
Maximum Occurance = 0 (45.50%)
Left Skewed at 0
Right Skewed Range = 180 to 547

69) EnclosedPorch
Continous Variable
Enclosed porch area in square feet
No NULL Values
Maximum Occurance = 0 (85.50%)

70) 3SsnPorch
Continous Variable
Three season porch area in square feet
No NULL Values
Maximum Occurance = 0 (98%)

71) ScreenPorch
Continous Variable
Screen porch area in square feet
No NULL Values
Maximum Occurance = 0 (92%)

72) PoolArea
Continous Variable
Pool area in square feet
No NULL Values
Maximum Occurance = 0 (99.40%)
7 other distinct values
Hence, WE SHALL DROP THIS COLUMN

73) PoolQC
Categorical Variable (Ordinal)
Pool quality
Null Values = 99.40%
3 distinct values with 7 entries only
Hence, WE SHALL DROP THIS COLUMN

74) Fence
Categorical Variable (Ordinal)
Fence quality
Null Values = 80%
Hence, WE SHALL DROP THIS COLUMN

75) MiscFeature
Categorical Variable
Miscellaneous feature not covered in other categories
Null Values = 96.25%
Hence, WE SHALL DROP THIS COLUMN

76) MiscVal
Numerical Value
$Value of miscellaneous feature
No NULL Values
Maximum Occurance = 0 (96.40%)
Since, the misc features does not contain much info
Also, MiscVal has above 96% 0 values
Hence, WE SHALL DROP THIS COLUMN

77) MoSold
Numerical Value (Discrete)
Month Sold (MM)
No NULL Values
Maximum Occurances =
6 (17.4%)
7 (16%)
5 (14.2%)
4 (9.7%)

78) YrSold
Numerical Value (Discrete)
Year Sold (YYYY)
No NULL Values
Maximum Occurances =
2007 (22.6%)
2009 (22.3%)
2006 (21.7%)
2008 (21.2%)
2010 (12.2%)

79) SaleType
Categorical Variable
Type of sale
No NULL Values
Maximum Occurance = WD (Warranty Deed - Conventional) (85.5%)

80) SaleCondition
Categorical Variable

Condition of sale
No NULL Values
Maximum Occurance = Normal (Normal Sale) (81%)

81) SalePrice (TARGET VARIABLE)
Continous Variable
No NULL Value
Range = 34900 to 755000

Data Sources and their formats

Data Description:-

MSSubClass: Identifies the type of dwelling involved in the sale.

20	1-STORY 1946 & NEWER ALL STYLES
30	1-STORY 1945 & OLDER
40	1-STORY W/FINISHED ATTIC ALL AGES
45	1-1/2 STORY - UNFINISHED ALL AGES
50	1-1/2 STORY FINISHED ALL AGES
60	2-STORY 1946 & NEWER
70	2-STORY 1945 & OLDER
75	2-1/2 STORY ALL AGES
80	SPLIT OR MULTI-LEVEL
85	SPLIT FOYER
90	DUPLEX - ALL STYLES AND AGES
120	1-STORY PUD (Planned Unit Development) - 1946 & NEWER
150	1-1/2 STORY PUD - ALL AGES
160	2-STORY PUD - 1946 & NEWER
180	PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
190	2 FAMILY CONVERSION - ALL STYLES AND AGES

MSZoning: Identifies the general zoning classification of the sale.

A	Agriculture
C	Commercial
FV	Floating Village Residential
I	Industrial
RH	Residential High Density
RL	Residential Low Density
RP	Residential Low Density Park
RM	Residential Medium Density

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

Grvl	Gravel
Pave	Paved

Alley: Type of alley access to property

Grvl	Gravel
Pave	Paved
NA	No alley access

LotShape: General shape of property

Reg	Regular
IR1	Slightly irregular
IR2	Moderately Irregular
IR3	Irregular

LandContour: Flatness of the property

Lvl	Near Flat/Level
Bnk	Banked - Quick and significant rise from street grade to building
HLS	Hillside - Significant slope from side to side
Low	Depression

Utilities: Type of utilities available

AllPub	All public Utilities (E,G,W,& S)
NoSewr	Electricity, Gas, and Water (Septic Tank)
NoSeWa	Electricity and Gas Only
ELO	Electricity only

LotConfig: Lot configuration

Inside	Inside lot
Corner	Corner lot
CulDSac	Cul-de-sac
FR2	Frontage on 2 sides of property
FR3	Frontage on 3 sides of property

LandSlope: Slope of property

Gtl	Gentle slope
Mod	Moderate Slope
Sev	Severe Slope

Neighborhood: Physical locations within Ames city limits

Blmngtn	Bloomington Heights
Blueste	Bluestem
BrDale	Briardale
BrkSide	Brookside
ClearCr	Clear Creek
CollgCr	College Creek
Crawfor	Crawford
Edwards	Edwards
Gilbert	Gilbert
IDOTRR	Iowa DOT and Rail Road
MeadowV	Meadow Village
Mitchel	Mitchell
Names	North Ames
NoRidge	Northridge
NPkVill	Northpark Villa
NridgHt	Northridge Heights
NWAmes	Northwest Ames
OldTown	Old Town
SWISU	South & West of Iowa State University
Sawyer	Sawyer
SawyerW	Sawyer West
Somerst	Somerset
StoneBr	Stone Brook
Timber	Timberland
Veenker	Veenker

Condition1: Proximity to various conditions

Artery	Adjacent to arterial street
Feedr	Adjacent to feeder street
Norm	Normal
RRNn	Within 200' of North-South Railroad
RRAn	Adjacent to North-South Railroad
PosN	Near positive off-site feature--park, greenbelt, etc.
PosA	Adjacent to postive off-site feature
RRNe	Within 200' of East-West Railroad
RRAe	Adjacent to East-West Railroad

Condition2: Proximity to various conditions (if more than one is present)

Artery	Adjacent to arterial street
Feedr	Adjacent to feeder street
Norm	Normal
RRNn	Within 200' of North-South Railroad
RRAn	Adjacent to North-South Railroad
PosN	Near positive off-site feature--park, greenbelt, etc.
PosA	Adjacent to postive off-site feature
RRNe	Within 200' of East-West Railroad
RRAe	Adjacent to East-West Railroad

BldgType: Type of dwelling

1Fam	Single-family Detached
2FmCon	Two-family Conversion; originally built as one-family dwelling
Duplx	Duplex
TwnhsE	Townhouse End Unit
TwnhsI	Townhouse Inside Unit

HouseStyle: Style of dwelling

1Story	One story
1.5Fin	One and one-half story: 2nd level finished
1.5Unf	One and one-half story: 2nd level unfinished
2Story	Two story
2.5Fin	Two and one-half story: 2nd level finished
2.5Unf	Two and one-half story: 2nd level unfinished
SFoyer	Split Foyer
SLvl	Split Level

OverallQual: Rates the overall material and finish of the house

10	Very Excellent
9	Excellent
8	Very Good
7	Good
6	Above Average
5	Average
4	Below Average
3	Fair
2	Poor
1	Very Poor

OverallCond: Rates the overall condition of the house

10	Very Excellent
9	Excellent
8	Very Good
7	Good
6	Above Average
5	Average
4	Below Average
3	Fair
2	Poor
1	Very Poor

YearBuilt: Original construction date
YearRemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

Flat	Flat
Gable	Gable
Gambrel	Gabrel (Barn)
Hip	Hip
Mansard	Mansard
Shed	Shed

RoofMatl: Roof material

ClyTile	Clay or Tile
CompShg	Standard (Composite) Shingle
Membran	Membrane
Metal	Metal
Roll	Roll
Tar&Grv	Gravel & Tar
WdShake	Wood Shakes
WdShngl	Wood Shingles

Exterior1st: Exterior covering on house

AsbShng	Asbestos Shingles
AsphShn	Asphalt Shingles
BrkComm	Brick Common
BrkFace	Brick Face
CBlock	Cinder Block
CemntBd	Cement Board
HdBoard	Hard Board
ImStucc	Imitation Stucco
MetalSd	Metal Siding
Other	Other
Plywood	Plywood
PreCast	PreCast
Stone	Stone
Stucco	Stucco
VinylSd	Vinyl Siding
Wd Sdng	Wood Siding

WdShing Wood Shingles

Exterior2nd: Exterior covering on house (if more than one material)

AsbShng Asbestos Shingles
AsphShn Asphalt Shingles
BrkComm Brick Common
BrkFace Brick Face
CBlock Cinder Block
CemntBd Cement Board
HdBoard Hard Board
ImStucc Imitation Stucco
MetalSd Metal Siding
Other Other
Plywood Plywood
PreCast PreCast
Stone Stone
Stucco Stucco
VinylSd Vinyl Siding
Wd Sdng Wood Siding
WdShing Wood Shingles

MasVnrType: Masonry veneer type

BrkCmn Brick Common
BrkFace Brick Face
CBlock Cinder Block
None None
Stone Stone

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

Ex Excellent
Gd Good
TA Average/Typical
Fa Fair
Po Poor

ExterCond: Evaluates the present condition of the material on the exterior

Ex Excellent
Gd Good
TA Average/Typical
Fa Fair
Po Poor

Foundation: Type of foundation

BrkTil Brick & Tile
CBlock Cinder Block
PConc Poured Contrete
Slab Slab
Stone Stone
Wood Wood

BsmtQual: Evaluates the height of the basement

- Ex Excellent (100+ inches)
- Gd Good (90-99 inches)
- TA Typical (80-89 inches)
- Fa Fair (70-79 inches)
- Po Poor (<70 inches
- NA No Basement

BsmtCond: Evaluates the general condition of the basement

- Ex Excellent
- Gd Good
- TA Typical - slight dampness allowed
- Fa Fair - dampness or some cracking or settling
- Po Poor - Severe cracking, settling, or wetness
- NA No Basement

BsmtExposure: Refers to walkout or garden level walls

- Gd Good Exposure
- Av Average Exposure (split levels or foyers typically score average or above)
- Mn Mimimum Exposure
- No No Exposure
- NA No Basement

BsmtFinType1: Rating of basement finished area

- GLQ Good Living Quarters
- ALQ Average Living Quarters
- BLQ Below Average Living Quarters
- Rec Average Rec Room
- LwQ Low Quality
- Unf Unfinshed
- NA No Basement

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

- GLQ Good Living Quarters
- ALQ Average Living Quarters
- BLQ Below Average Living Quarters
- Rec Average Rec Room
- LwQ Low Quality
- Unf Unfinshed
- NA No Basement

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

Floor	Floor Furnace
GasA	Gas forced warm air furnace
GasW	Gas hot water or steam heat
Grav	Gravity furnace
OthW	Hot water or steam heat other than gas
Wall	Wall furnace

HeatingQC: Heating quality and condition

Ex	Excellent
Gd	Good
TA	Average/Typical
Fa	Fair
Po	Poor

CentralAir: Central air conditioning

N	No
Y	Yes

Electrical: Electrical system

SBrkr	Standard Circuit Breakers & Romex
FuseA	Fuse Box over 60 AMP and all Romex wiring (Average)
FuseF	60 AMP Fuse Box and mostly Romex wiring (Fair)
FuseP	60 AMP Fuse Box and mostly knob & tube wiring (poor)
Mix	Mixed

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade
HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

Ex	Excellent
Gd	Good
TA	Typical/Average
Fa	Fair

Po Poor

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted)

Typ	Typical Functionality
Min1	Minor Deductions 1
Min2	Minor Deductions 2
Mod	Moderate Deductions
Maj1	Major Deductions 1
Maj2	Major Deductions 2
Sev	Severely Damaged
Sal	Salvage only

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

Ex	Excellent - Exceptional Masonry Fireplace
Gd	Good - Masonry Fireplace in main level
TA	Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement
Fa	Fair - Prefabricated Fireplace in basement
Po	Poor - Ben Franklin Stove
NA	No Fireplace

GarageType: Garage location

2Types	More than one type of garage
Attchd	Attached to home
Basment	Basement Garage
BuiltIn	Built-In (Garage part of house - typically has room above garage)
CarPort	Car Port
Detchd	Detached from home
NA	No Garage

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

Fin	Finished
RFn	Rough Finished
Unf	Unfinished
NA	No Garage

GarageCars: Size of garage in car capacity
GarageArea: Size of garage in square feet

GarageQual: Garage quality

Ex	Excellent
Gd	Good
TA	Typical/Average
Fa	Fair
Po	Poor

NA No Garage

GarageCond: Garage condition
- Ex Excellent
- Gd Good
- TA Typical/Average
- Fa Fair
- Po Poor
- NA No Garage

PavedDrive: Paved driveway
- Y Paved
- P Partial Pavement
- N Dirt/Gravel

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality
- Ex Excellent
- Gd Good
- TA Average/Typical
- Fa Fair
- NA No Pool

Fence: Fence quality
- GdPrv Good Privacy
- MnPrv Minimum Privacy
- GdWo Good Wood
- MnWw Minimum Wood/Wire
- NA No Fence

MiscFeature: Miscellaneous feature not covered in other categories
- Elev Elevator
- Gar2 2nd Garage (if not described in garage section)
- Othr Other
- Shed Shed (over 100 SF)
- TenC Tennis Court
- NA None

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

WD	Warranty Deed - Conventional
CWD	Warranty Deed - Cash
VWD	Warranty Deed - VA Loan
New	Home just constructed and sold
COD	Court Officer Deed/Estate
Con	Contract 15% Down payment regular terms
ConLw	Contract Low Down payment and low interest
ConLI	Contract Low Interest
ConLD	Contract Low Down
Oth	Other

SaleCondition: Condition of sale

Normal	Normal Sale
Abnorml	Abnormal Sale - trade, foreclosure, short sale
AdjLand	Adjoining Land Purchase
Alloca	Allocation - two linked properties with separate deeds, typically condo with a garage unit
Family	Sale between family members
Partial	Home was not completed when last assessed (associated with New Homes)

Data Preprocessing Done

i. Dropping Unnecessary Features
ii. Handling Null Values
iii. Handling Null Valued Rows
iv. Imputation
v. Encoding
vi. Dropping Highly Correlated Features
vii. Identifying & Removing Skewness
viii. Scaling the data

(i) Dropping Unnecessary Features

1) Id
This is just a pointer variable and not useful in predictive analysis.

6) Street
Type of road access to property
Maximum Occurance = Pave (Paved) (99.7%)

7) Alley
Type of alley access to property
Null Values = 1091 (93.50%)

10) Utilities
Type of utilities available
Maximum Occurance = AllPub (100%)

15) Condition2
Proximity to various conditions (if more than one is present)
Maximum Occurance = Norm (Normal) (99%)

23) RoofMat1
Roof material
Maximum Occurance = CompShg (Standard (Composite) Shingle) (98%)

40) Heating
Type of heating
Maximum Occurance = GasA (Gas forced warm air furnace) (98%)

46) LowQualFinSF
Low quality finished square feet (all floors)
Maximum Occurances = 0 (98%)

70) 3SsnPorch
Three season porch area in square feet
Maximum Occurance = 0 (98%)

71) ScreenPorch
Screen porch area in square feet
Maximum Occurance = 0 (92%)

72) PoolArea
Pool area in square feet
Maximum Occurance = 0 (99.40%)

73) PoolQC
Pool quality
Null Values = 99.40%

74) Fence
Fence quality

Null Values = 80%

75) MiscFeature
Miscellaneous feature not covered in other categories
Null Values = 96.25%

76) MiscVal
$Value of miscellaneous feature
Maximum Occurance = 0 (96.40%)

We shall drop the above mentioned features who either have 80-100% null values, or above 80% a single value

(ii) Handling Null (Missing) Values

- Following are the null values present in the features

FireplaceQu	551
LotFrontage	214
GarageCond	64
GarageType	64
GarageYrBlt	64
GarageFinish	64
GarageQual	64
BsmtExposure	31
BsmtFinType2	31
BsmtQual	30
BsmtFinType1	30
BsmtCond	30
MasVnrArea	7
MasVnrType	7

FireplaceQu

-The most number of null values is in FireplaceQu feature

-That is because in all the 551 (47%) entries, the no of fire places as per the feature Fireplaces=0

-#The quality of a fireplace cannot be filled when there is no fireplace present

-We cannot impute any other value as the FireplaceQu, where there is no fireplace present

-Hence, in order to not misguide the algorithm with a value; We shall drop the feature FireplaceQu

(iii) Handling Null Valued rows

Checking the location (rows) of the occurrence of null values in similar features

1. Features related to Garage
2. Features related to Basement
3. Features related to Veneer

- Using the following code to check the occurrence of null values for each feature

- df[df['GarageCond'].isnull() & df['GarageType'].isnull() & df['GarageYrBlt'].isnull() & df['GarageFinish'].isnull() & df['GarageQual'].isnull()]
- df[df['BsmtExposure'].isnull() & df['BsmtFinType2'].isnull() & df['BsmtQual'].isnull() & df['BsmtCond'].isnull() & df['BsmtFinType1'].isnull()]
- df[df['MasVnrType'].isnull() & df['MasVnrArea'].isnull()]

- The output of all the 3 codes states that the null values are occurring at the same row for all the similar features and hence we will be dropping the rows to avoid imputing arbitrary values for all the features.

(iv) IMPUTATION

LotFrontage	200
BsmtFinType2	1
BsmtExposure	1

- LotFrontage has 200 null values
- BsmtFinType2 & BsmtExposure each has 1 null value

(iv) IMPUTATION

(A) SIMPLE IMPUTER

- BsmtExposure & BsmtFinType2 both has 1 Null value each, hence we shall impute the values in those entries.
- To impute the null values in this feature, we shall apply Simple Imputer; we will impute the null values with their mode/most frequent

```
 from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='most_frequent')
columns = ['BsmtFinType2','BsmtExposure']
for i in columns:
imputer = imputer.fit(df[[i]])
df[i] = imputer.transform(df[[i]])
```

(iv) IMPUTATION

(B) ITERATIVE IMPUTER

- We will apply Iterative imputer for LotFrontage feature as there are 200 null entries in it and iterative imputer will apply regression to impute the values in it.
- We shall pass LotArea as the other parameter to the imputer

```
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
iter_impute = IterativeImputer()
ite_imp =
pd.DataFrame(np.round(iter_impute.fit_transform(df[['LotFrontag
e','LotArea']])),columns=['LotFrontage','LotArea'])
df[['LotFrontage','LotArea']]=ite_imp
```

(v) ENCODING

(A) LABEL ENCODER

- Label Encoder is applied where there is no particular order in each unique value in the column.
- For nominal variables there is no such order compulsion but in the case of ordinal variables there are orders to be maintained.
- Hence, we will apply label encoder for nominal variables.
- Let us first state nominal variables in a list.

```
nominal_var =
['MSZoning','LotConfig','Neighborhood','Condition1','RoofStyle','Exte
rior1st','Exterior2nd','MasVnrType','Foundation','CentralAir','Electric
al','GarageType','SaleType','SaleCondition']

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in nominal_var:
   df[i] = le.fit_transform(df[i])
```

(v) ENCODING

(B) ORDINAL ENCODER

- We shall apply ordinal encoder over ordinal variables.
- from sklearn.preprocessing import OrdinalEncoder

```
ordinal_var =
['LotShape','LandContour','LandSlope','ExterQual','ExterCond','BsmtQ
ual','BsmtCond','BsmtFinType1','BsmtFinType2','BldgType','BsmtExpo
sure','GarageFinish','HouseStyle','HeatingQC','KitchenQual','Function
al','GarageQual','GarageCond','PavedDrive']

ord_enc=OrdinalEncoder(categories=[['IR3','IR2','IR1','Reg'],['Low','HL
S','Bnk','Lvl'],['Gtl','Mod','Sev'],['Fa','TA','Gd','Ex'],['Fa','TA','Gd','Ex'],['
Fa','TA','Gd','Ex'],['Po','Fa','TA','Gd'],['Unf','LwQ','Rec','BLQ','ALQ','GL
Q'],['Unf','LwQ','Rec','BLQ','ALQ','GLQ'],['1Fam','2fmCon','Duplex','Tw
nhsE','Twnhs'],['No','Mn','Av','Gd'],['Unf','RFn','Fin'],['1Story','1.5Fin','
1.5Unf','2Story','2.5Fin','2.5Unf','SFoyer','SLvl'],['Po','Fa','TA','Gd','Ex']
,['Fa','TA','Gd','Ex'],['Sev','Maj2','Maj1','Mod','Min2','Min1','Typ'],['Po'
,'Fa','TA','Gd','Ex'],['Po','Fa','TA','Gd','Ex'],['N','P','Y']])

df1=ord_enc.fit_transform(df[ordinal_var])

df[ordinal_var]=df1
```

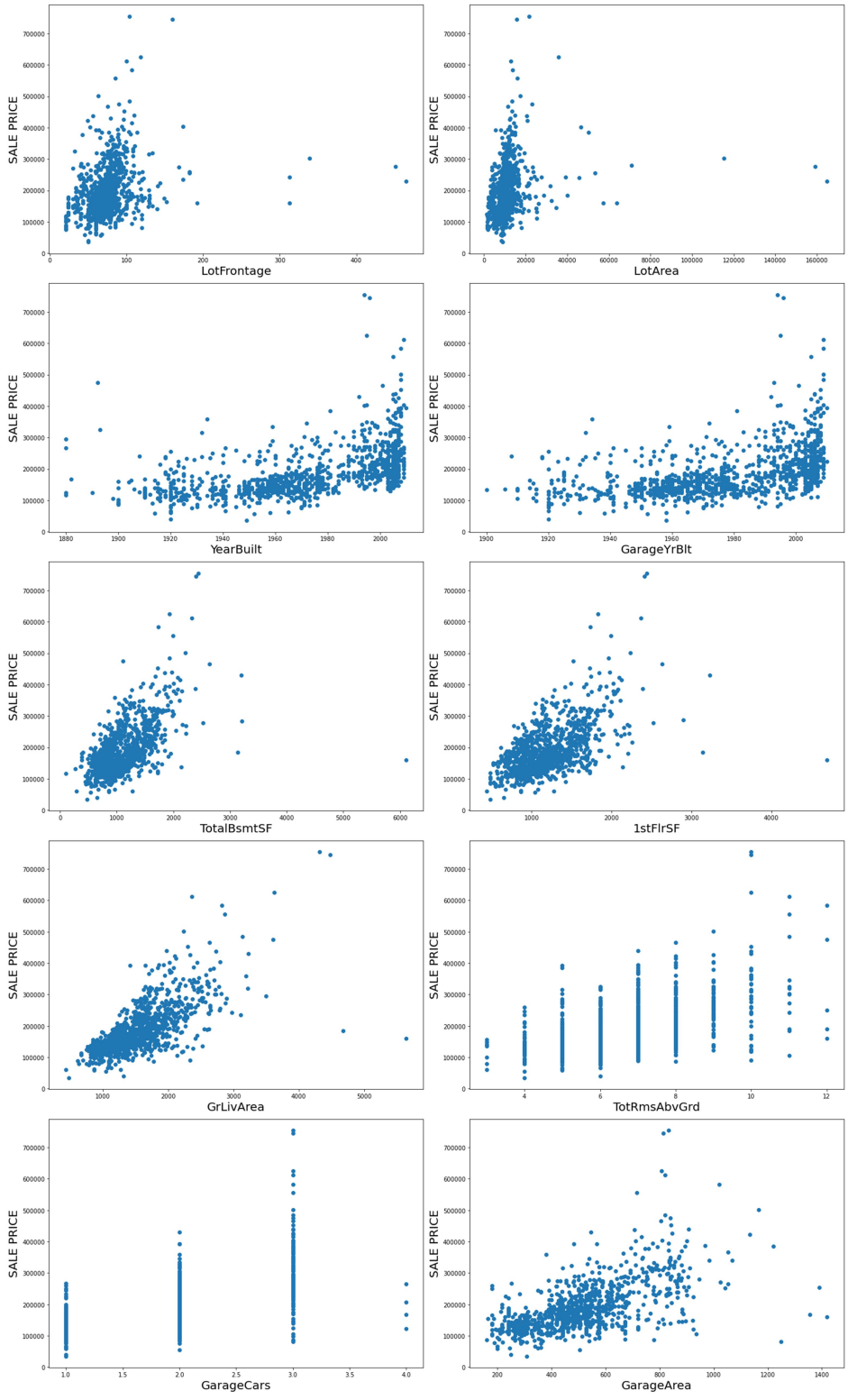
(vi) DROPPING HIGHLY CORRELATED FEATURES

- Let us check the correlation between each of the columns using df.corr() and heatmap

	Column 1	Column 2	Correlation
0	LotArea	LotFrontage	0.780968
1	BldgType	MSSubClass	0.759657
2	Exterior2nd	Exterior1st	0.867316
3	ExterQual	OverallQual	0.722725
4	Foundation	YearBuilt	0.723491
5	BsmtQual	YearBuilt	0.721840
6	BsmtFinSF2	BsmtFinType2	0.794346
7	1stFlrSF	TotalBsmtSF	0.887285
8	GrLivArea	2ndFlrSF	0.684365
9	KitchenQual	ExterQual	0.695937
10	TotRmsAbvGrd	GrLivArea	0.820955
11	GarageYrBlt	YearBuilt	0.826340
12	GarageArea	GarageCars	0.825041
13	SalePrice	OverallQual	0.779017
14	SalePrice	GrLivArea	0.707641

(vi) DROPPING HIGHLY CORRELATED FEATURES

- Checking the relation between highly correlated numerical features vs label :-



-

(vi) DROPPING HIGHLY CORRELATED FEATURES

- Observations from the scatter plot b/w numerical variables and target variable :-

(#**1) LotArea LotFrontage 0.780968**

LotArea seems to have a better relationship with the target variable

(#2) **GarageYrBlt YearBuilt 0.826340**

Both have same relation,we will drop GarageYrBlt
as YearBuilt is about the entire house and GarageYrBlt is only about the Garage

(#3) **1stFlrSF TotalBsmtSF 0.887285**

TotalBsmtSF has a little better relation

(#4) **TotRmsAbvGrd GrLivArea 0.820955**

GrLivArea has better relationship

(#5) **GarageArea GarageCars 0.825041**

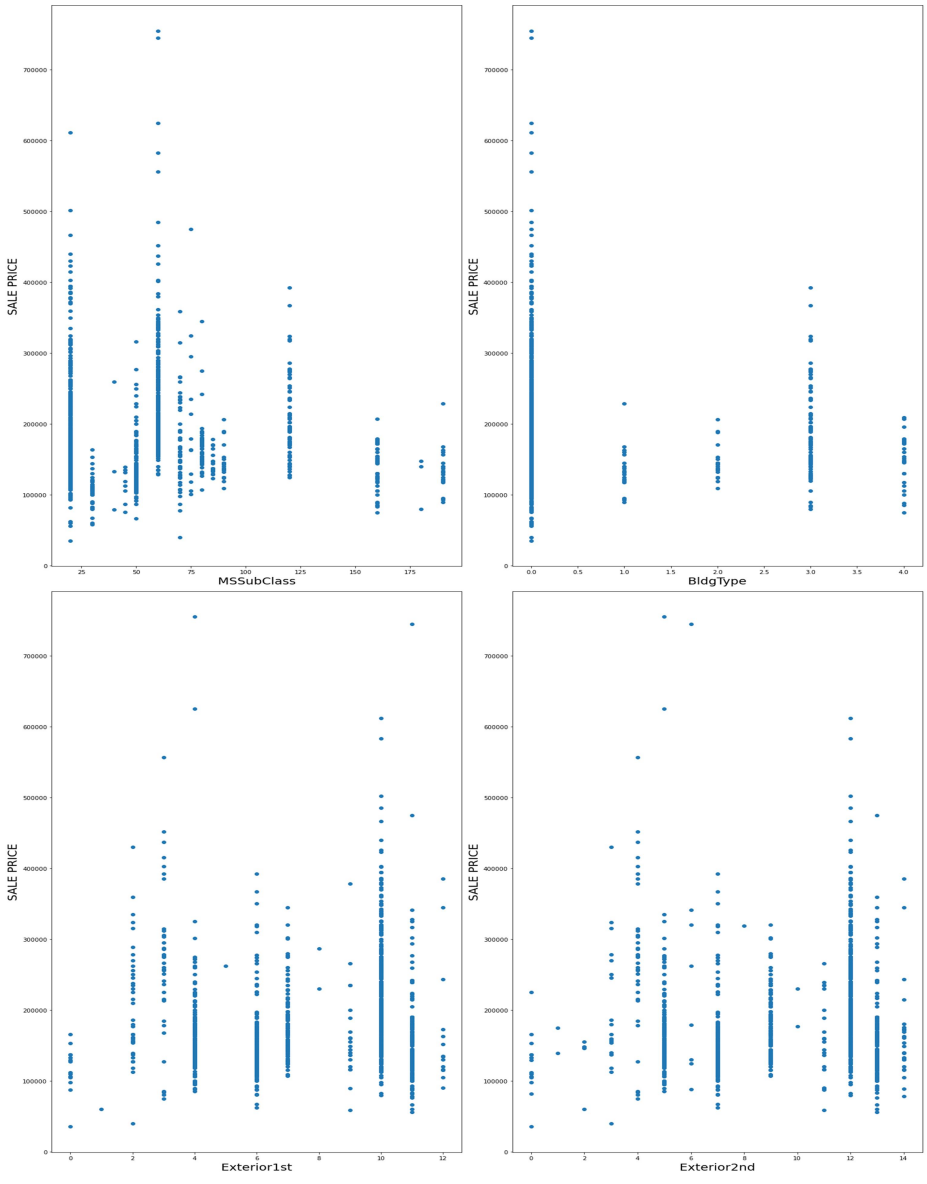
GarageArea has a better relationship

(#6) **BsmtFinSF2 BsmtFinType2 0.794346**

BsmtFinSF2 has a better relationship

(vi) DROPPING HIGHLY CORRELATED FEATURES

- Checking the relation between highly correlated categorical features vs label :-



Observations from the plot :-

#1 **BldgType MSSubClass 0.759657**

MSSubClass has a better relationship

#2 **Exterior2nd Exterior1st 0.867316**

Both have the same relationship, hence shall drop Exterior2nd

Just as they both denote similar thing

(vi) DROPPING HIGHLY CORRELATED FEATURES

- Cross Checking the important features to be selected by applying SelectKBest Feature Selection method

```
X=df.drop(columns=['SalePrice'])
y=df['SalePrice']
#Using SelectKBest feature seleciton Method
from sklearn.feature_selection import SelectKBest,f_classif
best_features=SelectKBest(f_classif, k=64)
fit=best_features.fit(X,y)
df_scores=pd.DataFrame(fit.scores_)
df_columns=pd.DataFrame(X.columns)
#concatenate dataframes
feature_scores = pd.concat([df_columns,df_scores],axis=1)
#name output columns
feature_scores.columns = ['Feaure_Name','Score']
#print 64 best features
top_features = feature_scores.nlargest(64,'Score')
print(feature_scores.nlargest(64,'Score'))
```

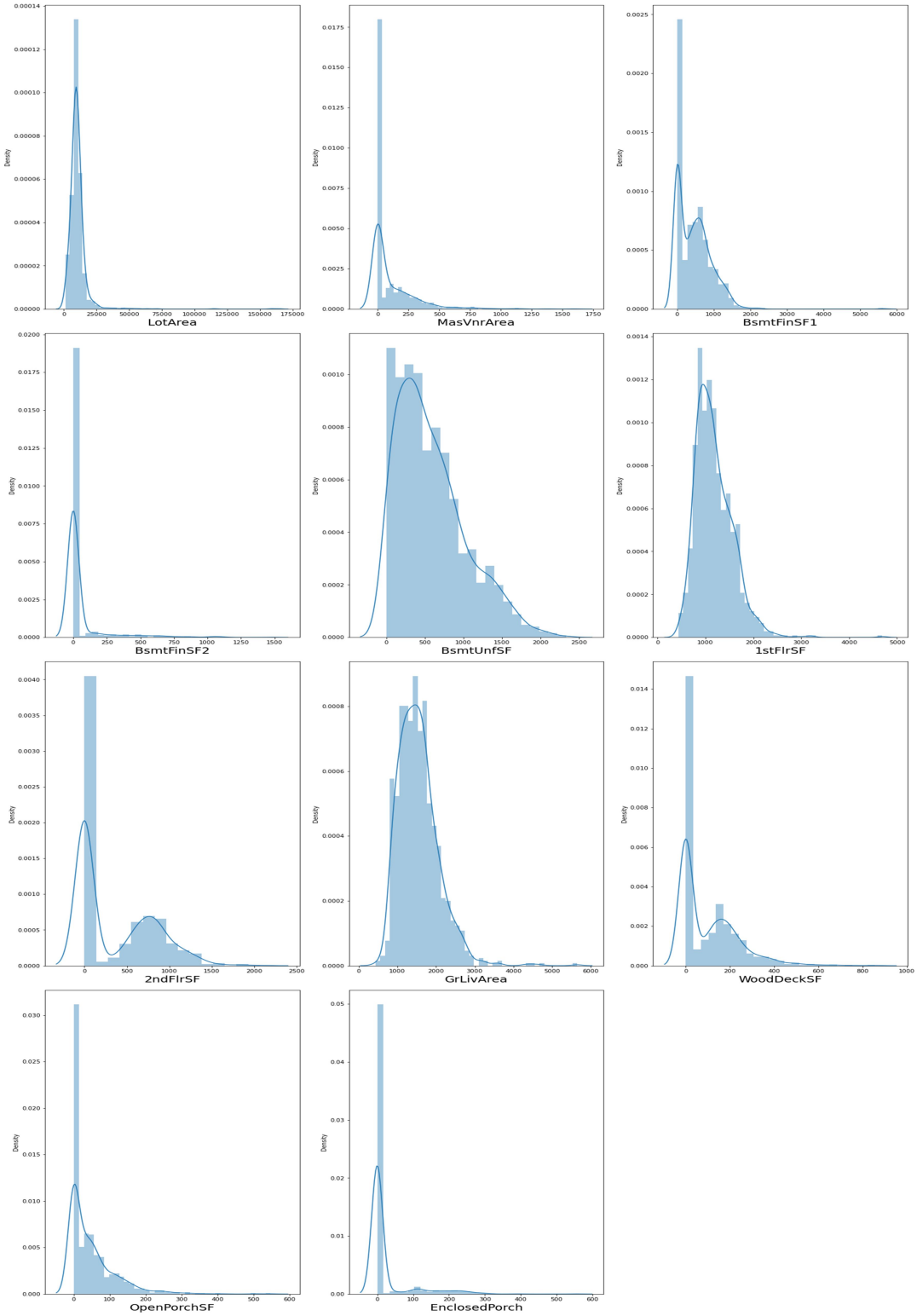
	Feaure_Name	Score
12	OverallQual	4.747910
21	ExterQual	3.259307
38	GrLivArea	2.954923
24	BsmtQual	2.847734
52	GarageCars	2.643168
45	KitchenQual	2.626759
53	GarageArea	2.433871
41	FullBath	2.376510
14	YearBuilt	2.051761
51	GarageFinish	2.027534
36	1stFlrSF	2.019970
1	MSZoning	1.885823
20	MasVnrArea	1.819184
3	LotArea	1.796031
46	TotRmsAbvGrd	1.785058
50	GarageYrBlt	1.778418
15	YearRemodAdd	1.749293
32	TotalBsmtSF	1.600719

(vi) DROPPING HIGHLY CORRELATED FEATURES

- From the above observations taken from the correlation chart and feature importance by applying SelectKBest we are dropping the following features :-
- columns_drop=['LotFrontage','GarageYrBlt','TotalBsmtSF','TotRmsAbvGrd','GarageArea','BsmtFinType2','MSSubClass','Exterior 2nd']
- df.drop(columns=columns_drop,inplace=True)
- df.shape
- (1073, 57)

(vii) Identifying & Removing Skewness

- Checking the distribution of the continuous variables via distribution plot



(vii) Identifying & Removing Skewness

- LotArea = High values of 0,right skewed
- MasVnrArea = High values of 0, righ skewed
- BsmtFinSF1 = High values of 0, right skewed
- BsmtFinSF2 = Very high values of 0, right skewed
- BsmtUnfSF = Slightly skewed
- 1stFlrSF = Slightly Skewed
- 2ndFlrSF = Very high values of 0, right skewed
- GrLivArea = right skewed
- WoodDeckSF = Very high values of 0, right skewed
- OpenPorchSF = Very high values of 0, right skewed
- EnclosedProch = Very high values of 0, right skewed

(vii) Identifying & Removing Skewness

- We will then check the skewness of the continuous variables by applying the .skew() method

- #Checking skewness of the features

```
df[cont_columns].skew().sort_values(ascending=False)
```

```
LotArea          10.487467
BsmtFinSF2        4.194615
EnclosedPorch     3.173403
MasVnrArea        2.741196
OpenPorchSF       2.279292
BsmtFinSF1        1.896087
1stFlrSF          1.548317
GrLivArea         1.523000
WoodDeckSF        1.457280
BsmtUnfSF         0.912966
2ndFlrSF          0.773012
```

- As we can observe from the above output that
- LoArea has very high value of skewness
- BsmfFinSF2, EnclosedProch, MasVnrArea, OpenPorchSF, BsmtFinsF1, 1stFlrSF, GrLivArea, WoodDeckSF too have high skewness

- We will now apply Powertransformer() to reduce the skewness in the continuous variables.

#We can see skewness in few of our columns, we will remove the skewness using power_transform function

```
from sklearn.preprocessing import power_transform
```

```
df_cont_new = power_transform(df_cont)
```

```
df_cont=pd.DataFrame(df_cont_new,columns=df_cont.columns)
```

(vii) Identifying & Removing Skewness

- Checking the skewness post transformation

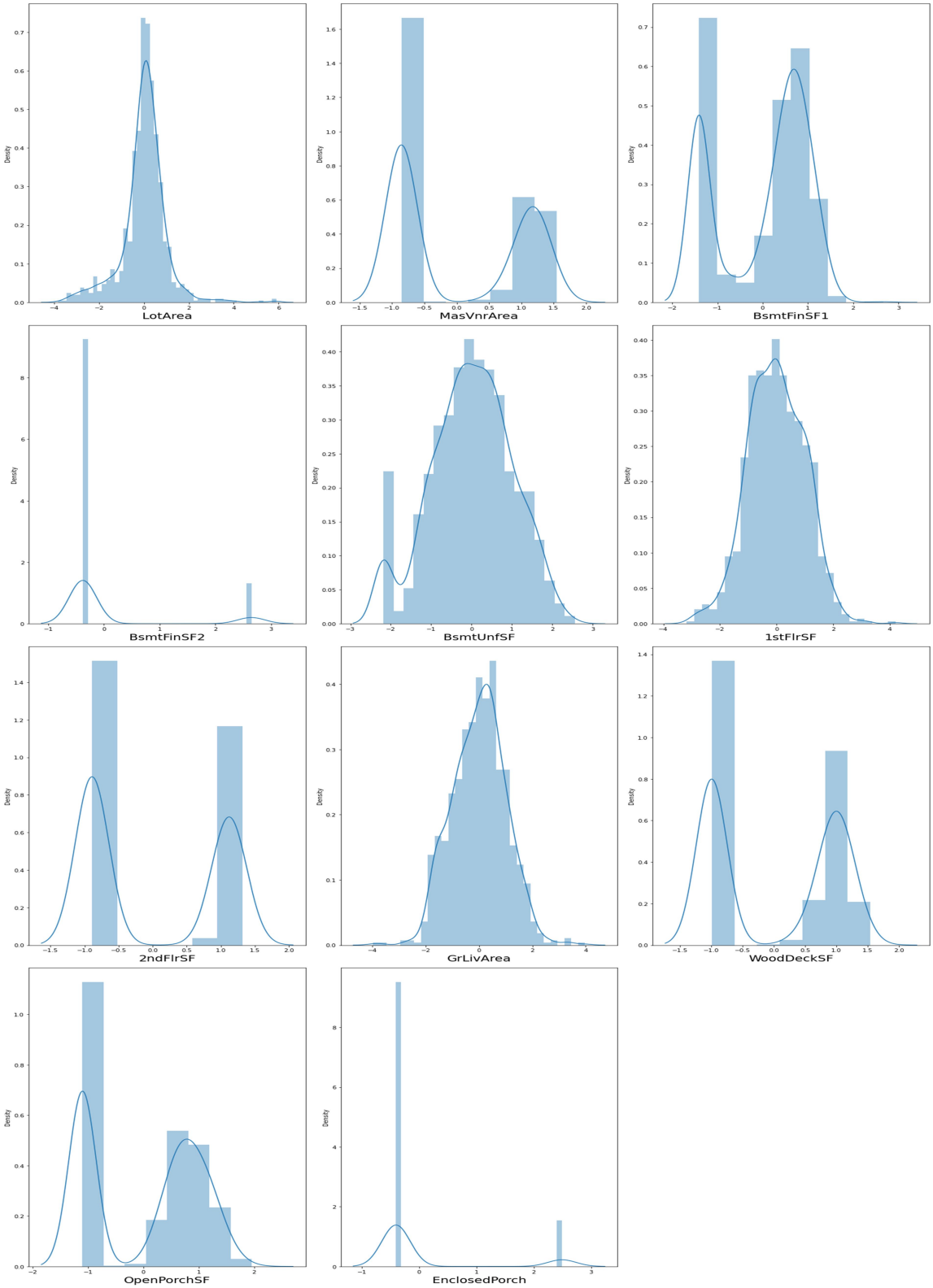
df_cont.skew().sort_values(ascending=False)

BsmtFinSF2	2.272586
EnclosedPorch	2.091618
MasVnrArea	0.342459
2ndFlrSF	0.238574
WoodDeckSF	0.046709
LotArea	0.017153
1stFlrSF	-0.001877
GrLivArea	-0.002211
OpenPorchSF	-0.056293
BsmtUnfSF	-0.199883
BsmtFinSF1	-0.453465

- BsmtFinsSF2, EnclosedPorch have skewness left only rest all the features do not have skewness left in them

(vii) Identifying & Removing Skewness

- Validating the skewness using distribution plot



(viii)Scaling the data

- Dividing into Feature and label
  X=df.drop(columns=['SalePrice'])
  y=df['SalePrice']

- Scaling the Features using StandardScaler()

  scaler = StandardScaler()

  X= scaler.fit_transform(X)

Data Inputs- Logic- Output Relationships

- As per the output of the correlation matrix , following two features are highly correlated with the output.

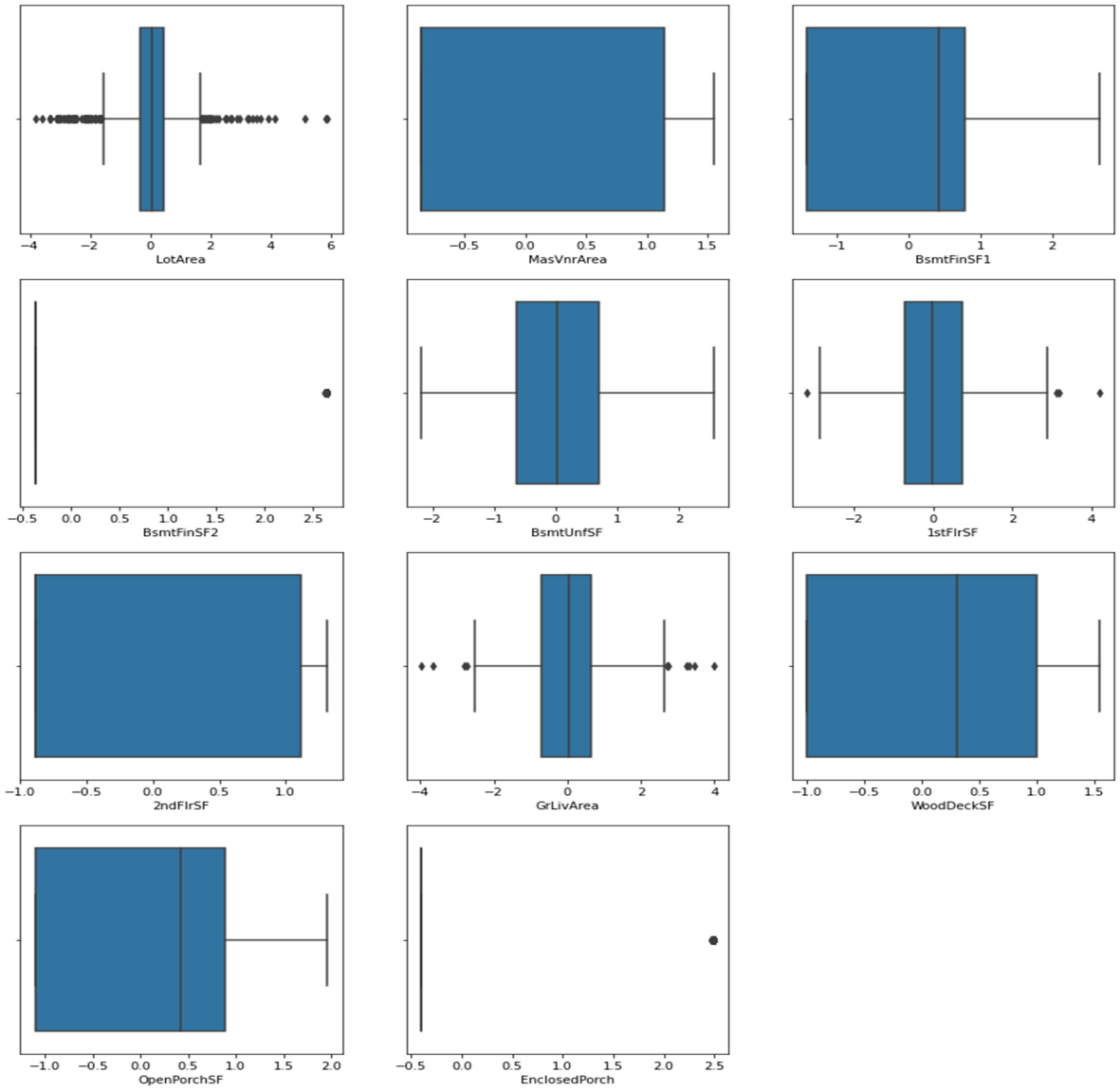
- 8 SalePrice OverallQual(4.75) 0.779017
- 9 SalePrice GrLivArea (2.95) 0.707641

- OverallQual has a positive correlation with SalePrice of 0.78
- GrLivArea has a positive correlation with SalePrice of 0.71

- According to the SelectKBest Feature Selection Method,
- OverallQual has an importance rating of 4.75
- GrLivArea has an importance rating of 2.95

- As per the above observation, both OverallQual & GrLivArea are important in predicting the SalePrice output and are also positive correlated with the output.

State the set of assumptions (if any) related to the problem under consideration



- LotArea has a lot of outliers in it, but because this feature describes the lot size in square feet there would be many houses with different lot sizes and hence we should not drop that data.
- That is why, we will move ahead with our modelling

Hardware and Software Requirements and Tools Used

- Following are the libraries imported for the successful implementation of the project

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
import xgboost as xgb
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split,cross_val_score,GridSearchCV
from sklearn.feature_selection import SelectKBest,f_classif
import seaborn as sns
import matplotlib.pyplot as plt
import pickle
import warnings
warnings.filterwarnings('ignore')
```

- Pandas used to import the dataset
- Numpy used mathematical calculations
- LinearRegression, LogisticRegression, DecisionTreeRegressor, RandomForestRegressor, AdaBoostRegressor, XGBoostRegressor used for building Machine Learning Model
- StandardScaler for data scaling
- Train_test_split to split the dataset into training & testing data
- Cross_val_score used for cross validation of the ML Model
- GridSearchCV used for HyperParameterTuning of the Selected Model
- SelectKBest, f_classif for feature selection
- Seaborn & matplotlib for visualization
- Pickle to save the model

Model/s Development and Evaluation

Testing of Identified Approaches (Algorithms)

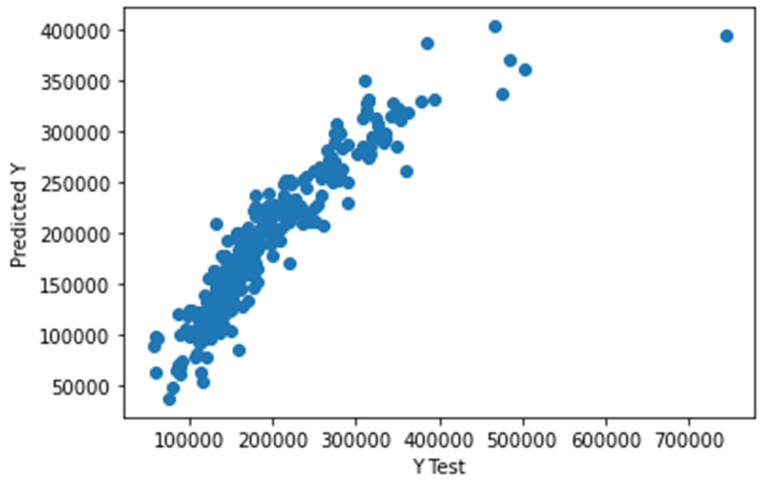
- LinearRegression,
- LogisticRegression,
- DecisionTreeRegressor,
- RandomForestRegressor,
- AdaBoostRegressor,
- XGBoostRegressor

Run and Evaluate selected models

Linear Regressor

```
#Linear Regression
lr.fit(x_train,y_train)
y_pred=lr.predict(x_test)
r2score=r2_score(y_test,y_pred)*100
print("R2Score :",r2score)
scr = cross_val_score(lr,X,y,cv=5)
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('RMSE:',rmse )
model_name.append('Linear Regression')
r2_scores.append(r2score)
rmse_value.append(rmse)
cvs.append(scr.mean())
plt.scatter(x=y_test,y=y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

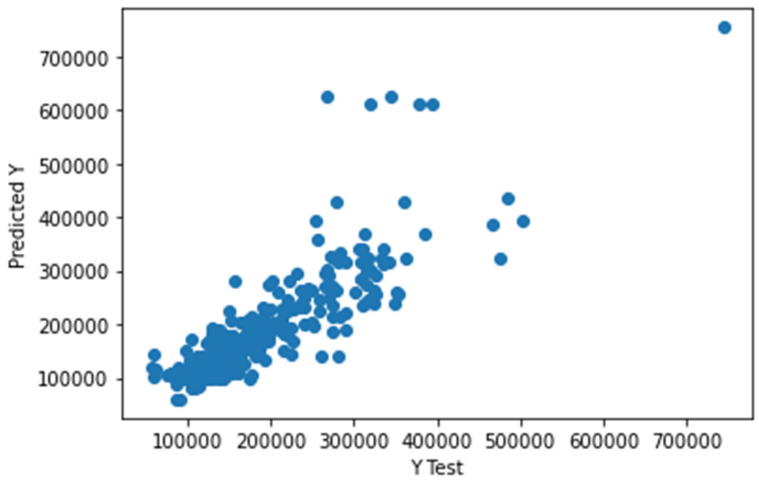
```
R2Score : 83.26743877122628
MAE: 21562.02620551029
MSE: 1137641909.7416432
RMSE: 33728.94765244897

Text(0, 0.5, 'Predicted Y')
```



Decision Tree Regressor

```
#Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor
dtr=DecisionTreeRegressor()
dtr.fit(x_train,y_train)
y_pred=dtr.predict(x_test)
r2score=r2_score(y_test,y_pred)*100
scr2 = cross_val_score(dtr,X,y,cv=5)
print("R2Score:", r2score)
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('RMSE:',rmse )
model_name.append('Decision Tree Regressor')
r2_scores.append(r2score)
rmse_value.append(rmse)
cvs.append(scr2.mean())
plt.scatter(x=y_test,y=y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

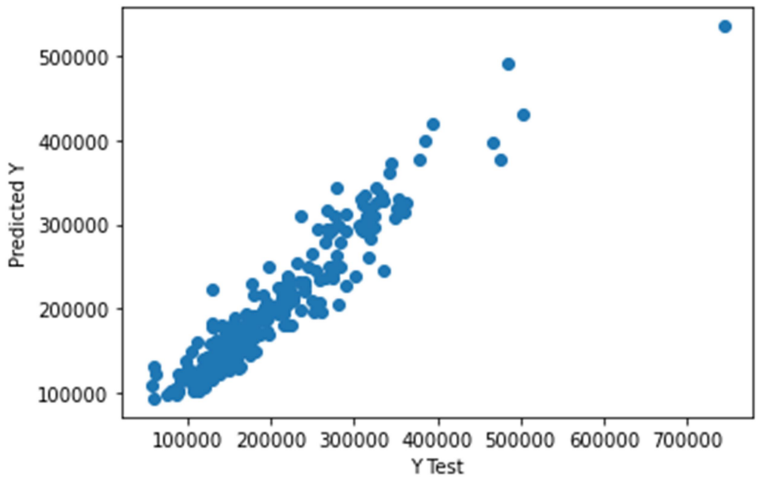
```
R2Score: 60.50504061655463
MAE: 31188.14596273292
MSE: 2685250656.121118
RMSE: 51819.40424320911

Text(0, 0.5, 'Predicted Y')
```



Random Forest Regressor

```
#RandomForest Regressor
from sklearn.ensemble import RandomForestRegressor
rdr = RandomForestRegressor()
rdr.fit(x_train,y_train)
y_pred=rdr.predict(x_test)
r2score=r2_score(y_test,y_pred)*100
scr3 = cross_val_score(rdr,X,y,cv=5)
print("R2Score: ", r2score)
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('RMSE:',rmse )
model_name.append('Random Forest Regressor')
r2_scores.append(r2score)
rmse_value.append(rmse)
cvs.append(scr3.mean())
plt.scatter(x=y_test,y=y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

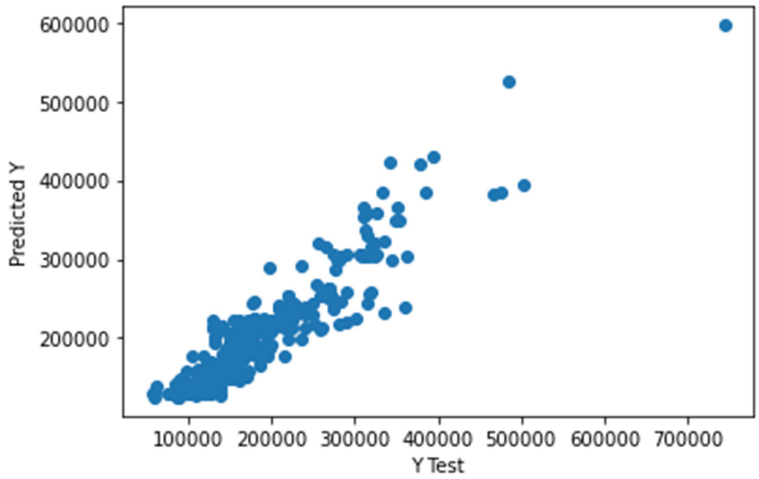
```
R2Score:  89.67972643266842
MAE: 16993.891304347828
MSE: 701672360.2364938
RMSE: 26489.098894384722

Text(0, 0.5, 'Predicted Y')
```



ADA Boost Regressor

```
from sklearn.ensemble import AdaBoostRegressor
ada = AdaBoostRegressor()
ada.fit(x_train,y_train)
y_pred=ada.predict(x_test)
r2score=r2_score(y_test,y_pred)*100
print("R2 Score: ", r2score)
scr5 = cross_val_score(ada,X,y,cv=5)
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('RMSE:',rmse )
model_name.append('ADA Boost')
r2_scores.append(r2score)
rmse_value.append(rmse)
cvs.append(scr5.mean())
plt.scatter(x=y_test,y=y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

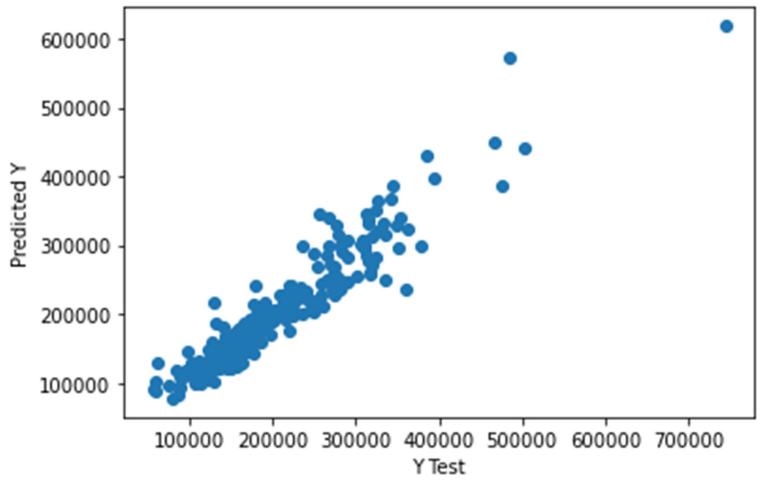
```
R2 Score:  81.3534023870281
MAE: 26995.965413792863
MSE: 1267776679.7665539
RMSE: 35605.85176296944

Text(0, 0.5, 'Predicted Y')
```



XGBoost Regressor

```
#XGB
import xgboost as xgb
xgb = xgb.XGBRegressor()
xgb.fit(x_train,y_train)
y_pred = xgb.predict(x_test)
r2score=r2_score(y_test,y_pred)*100
print("R2 Score: ",r2score)
scr6 = cross_val_score(xgb,X,y,cv=5)
from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
print('RMSE:',rmse )
model_name.append('XGBoost')
r2_scores.append(r2score)
rmse_value.append(rmse)
cvs.append(scr6.mean())
plt.scatter(x=y_test,y=y_pred)
plt.xlabel('Y Test')
plt.ylabel('Predicted Y')
```

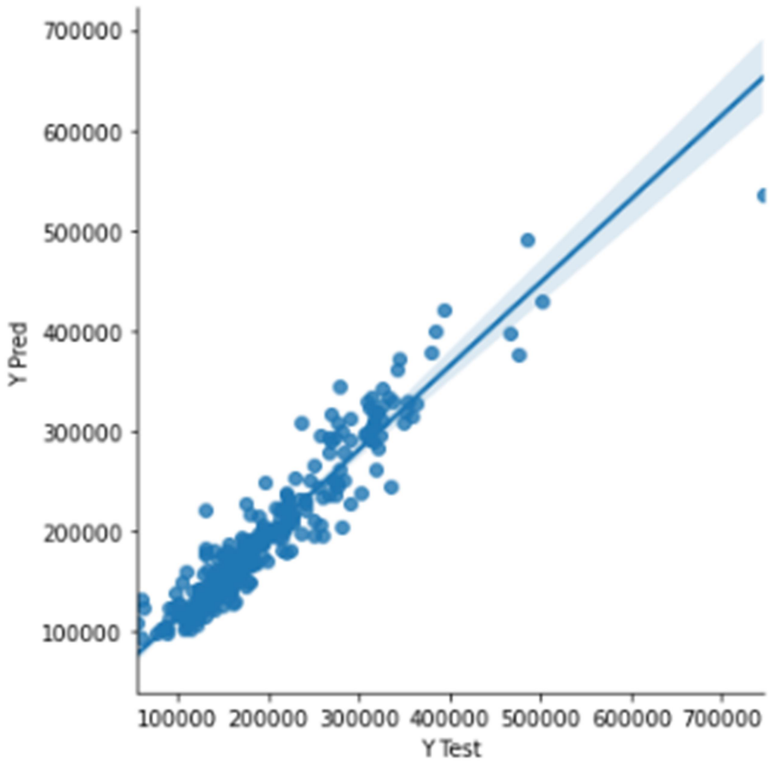
```
R2 Score:  90.45408926008322
MAE: 16857.379294448758
MSE: 649023659.6718593
RMSE: 25475.942763161078

Text(0, 0.5, 'Predicted Y')
```



MODEL DASHBOARD

	Model Name	r2 Score	RMSE	Cross Val Score
0	Linear Regression	83.267439	33728.947652	0.783417
1	Decision Tree Regressor	60.505041	51819.404243	0.720655
2	Random Forest Regressor	89.679726	26489.098894	0.838131
3	ADA Boost	81.353402	35605.851763	0.785783
4	XGBoost	90.454089	25475.942763	0.832870

- **Random Forest Regressor has 89.68 r2score and 0.84 as its cv score.**
-

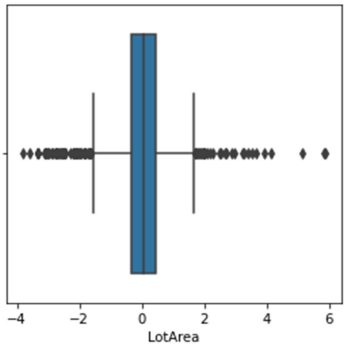


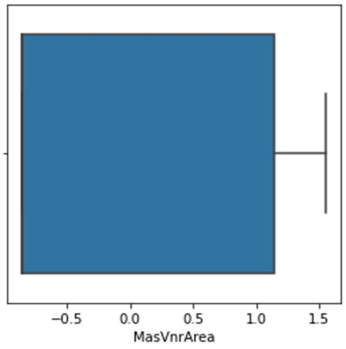
Key Metrics for success in solving problem under consideration

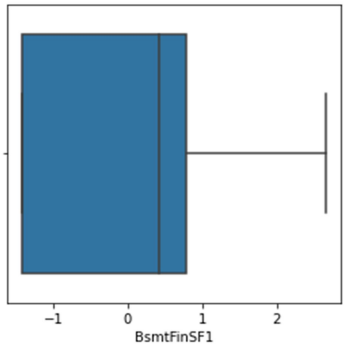
- **Data Cleaning**
- **Data Exploration & Analysis**
- **Feature Engineering**

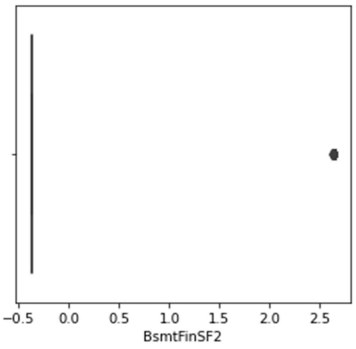
Visualizations

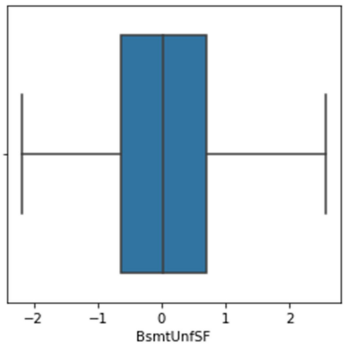
- Box Plot

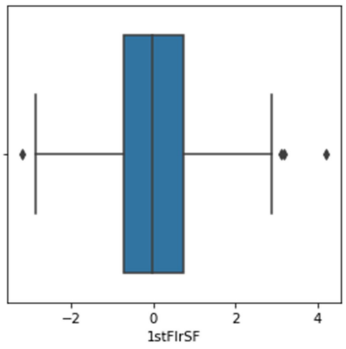


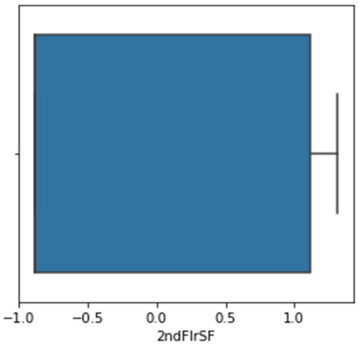


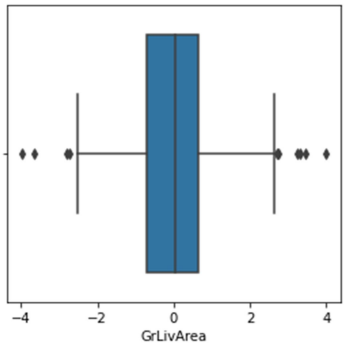


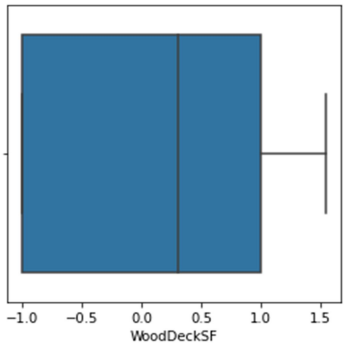


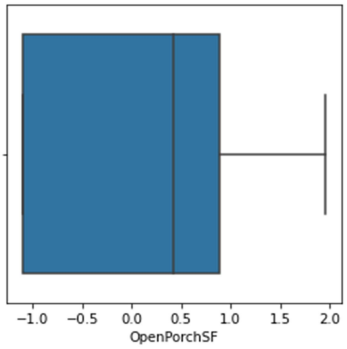


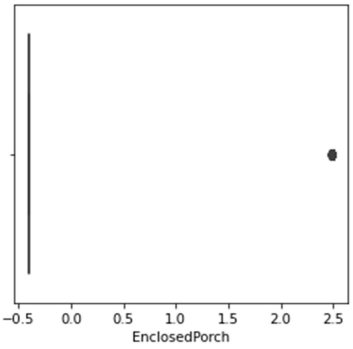




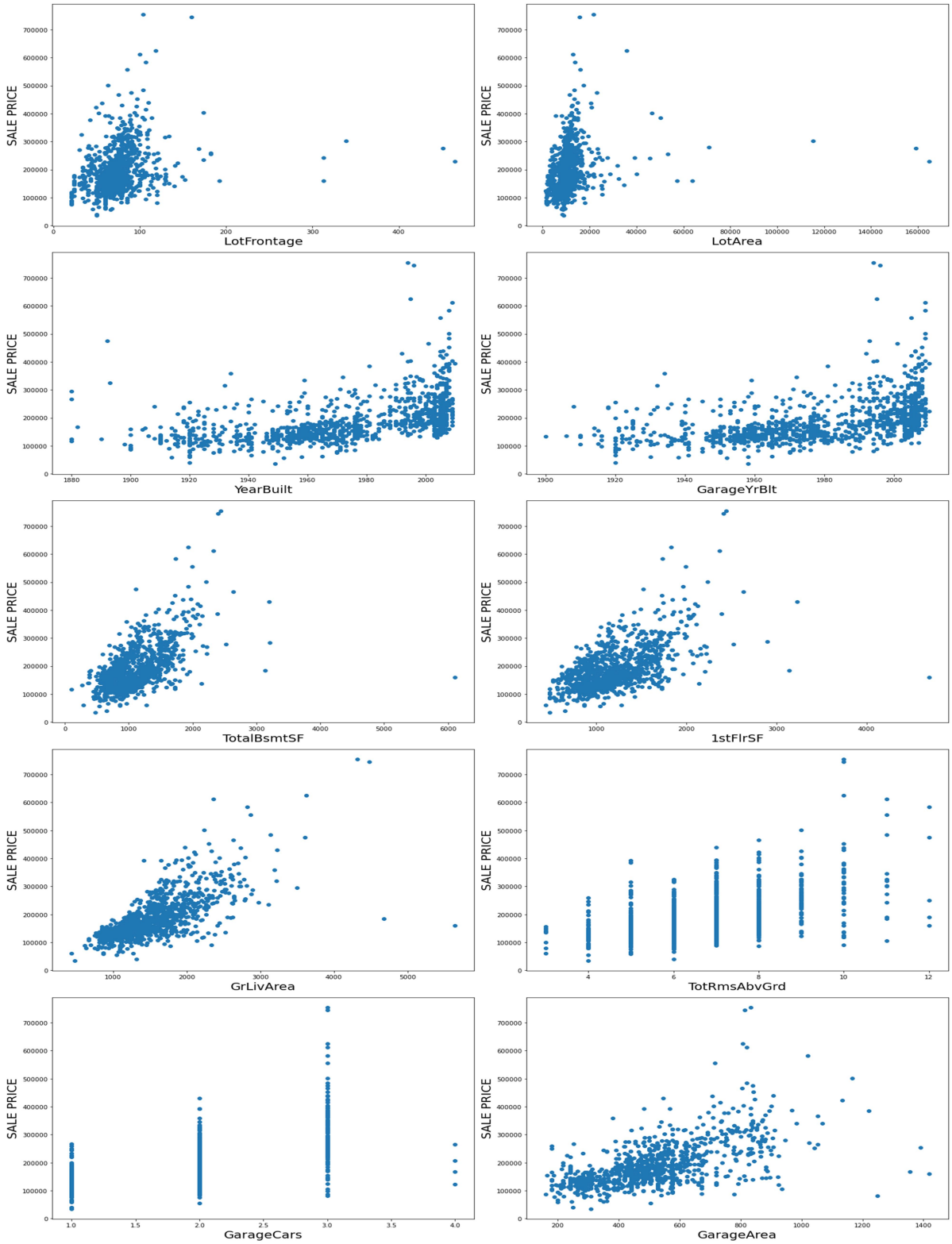




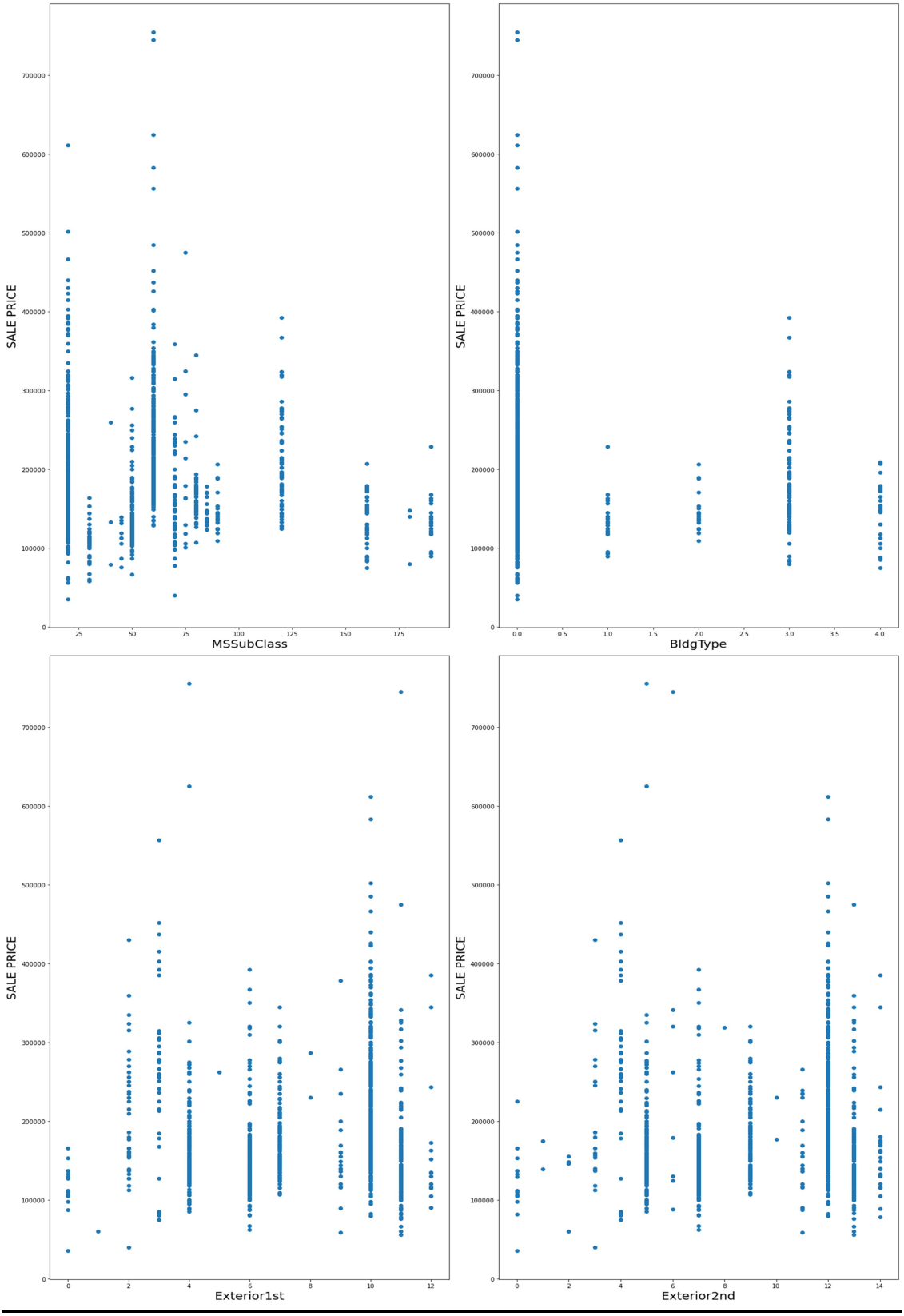




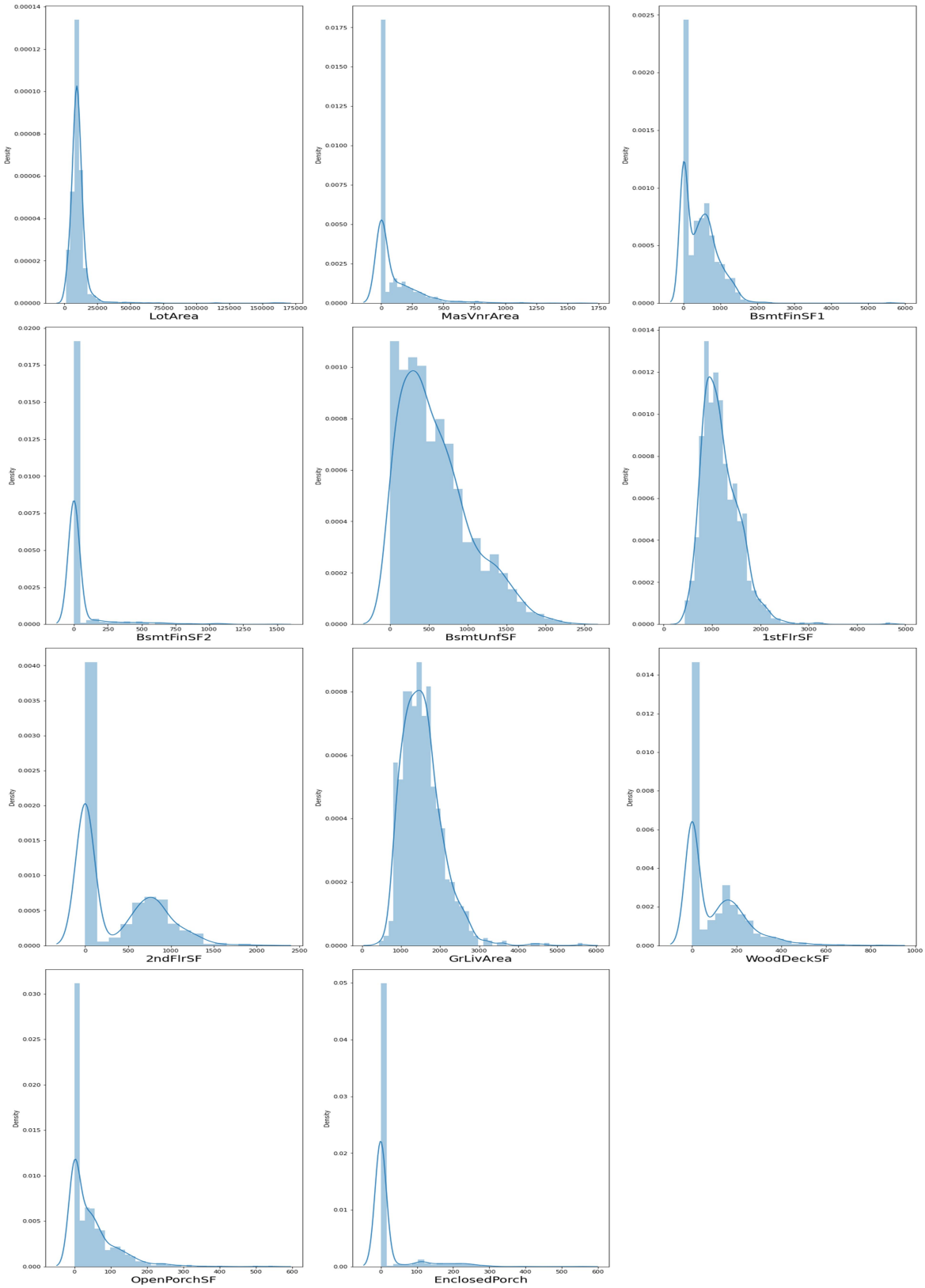
Scatter Plot



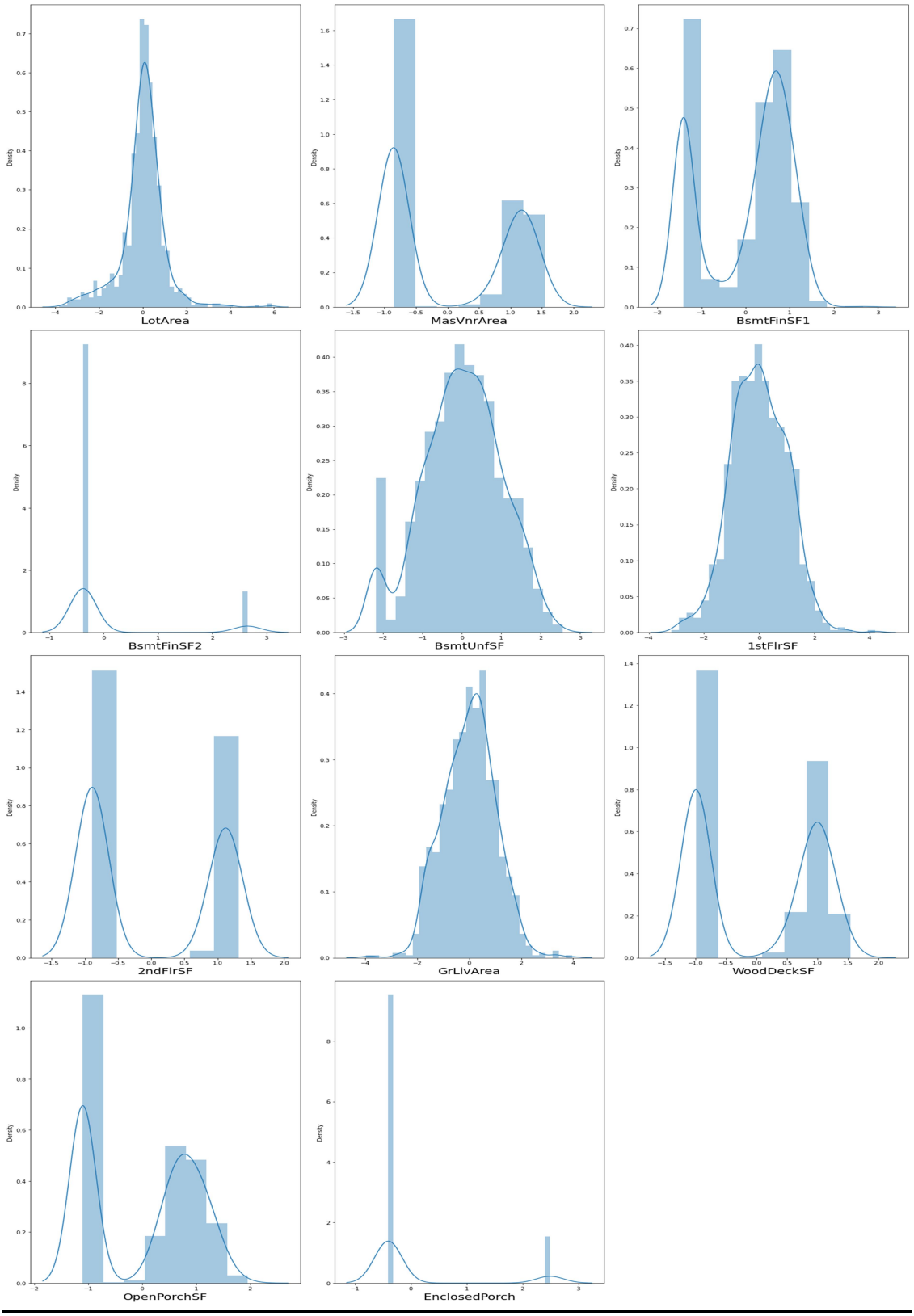
Scatter Plot



Distribution Plot



Distribution Plot



CONCLUSION

Key Findings and Conclusions of the Study

- OverallQuality of the house is the most important feature in predicting the SalesPrice
- RandomForestRegressor is the best Model for prediction

Learning Outcomes of the Study in respect of Data Science

Visualization:-

- From Visualization methods, we can easily check the skewness of the data, outliers and the relation between the features and label variable.
- From Visualization methods without even looking at the data entirely we can easily check many important features about the independent and dependent variables

Data Cleaning:-

- While Cleaning the data the entire knowledge about the dataset is very necessary as to understand what each column stands for, the datatype of each column
- In Data cleaning, it is very important to encode the data as per its datatype
- In Data Cleaning, handling null values and dropping columns is the most important aspect where the study, analysis of the dataset and domain knowledge comes into picture.
- Removing skewness and outliers from the dataset is the next most important aspect of handling the features, which can affect the model accuracy in many ways.

Challenges Faced:-

- The biggest challenge faced was while handling the test dataset.
- As the test dataset was also not cleaned and encoding the categorical features as per the same codes as done with training dataset was difficult.
- There were few distinct values in the columns absent in the training dataset present in the test dataset which needed to encoded similar to the training dataset.
- Hence, we could not encode the dataset directly as we did with the training dataset by using label encoder.
- The test dataset was first cleaned, handled missing values, encoded, scaled, feature engineering was done same as the training dataset and then the prediction of the output was done by using the same trained model with the training dataset.

Limitations of this work and Scope for Future Work

The solution provided is limited to the type and details of the dataset used in this project.

To further extend this study and improve the results, more such similar datasets can be used during the training and testing phase.