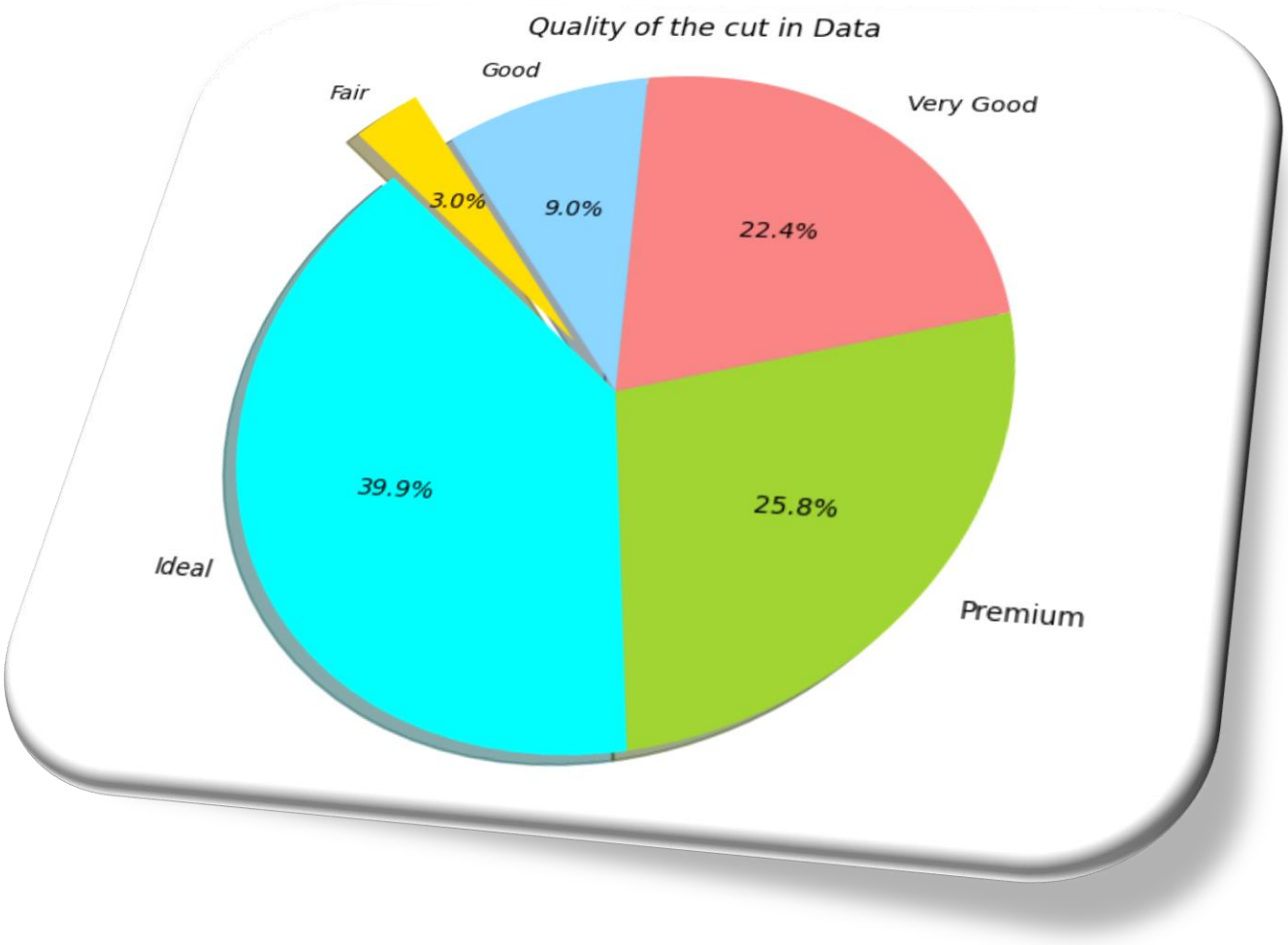
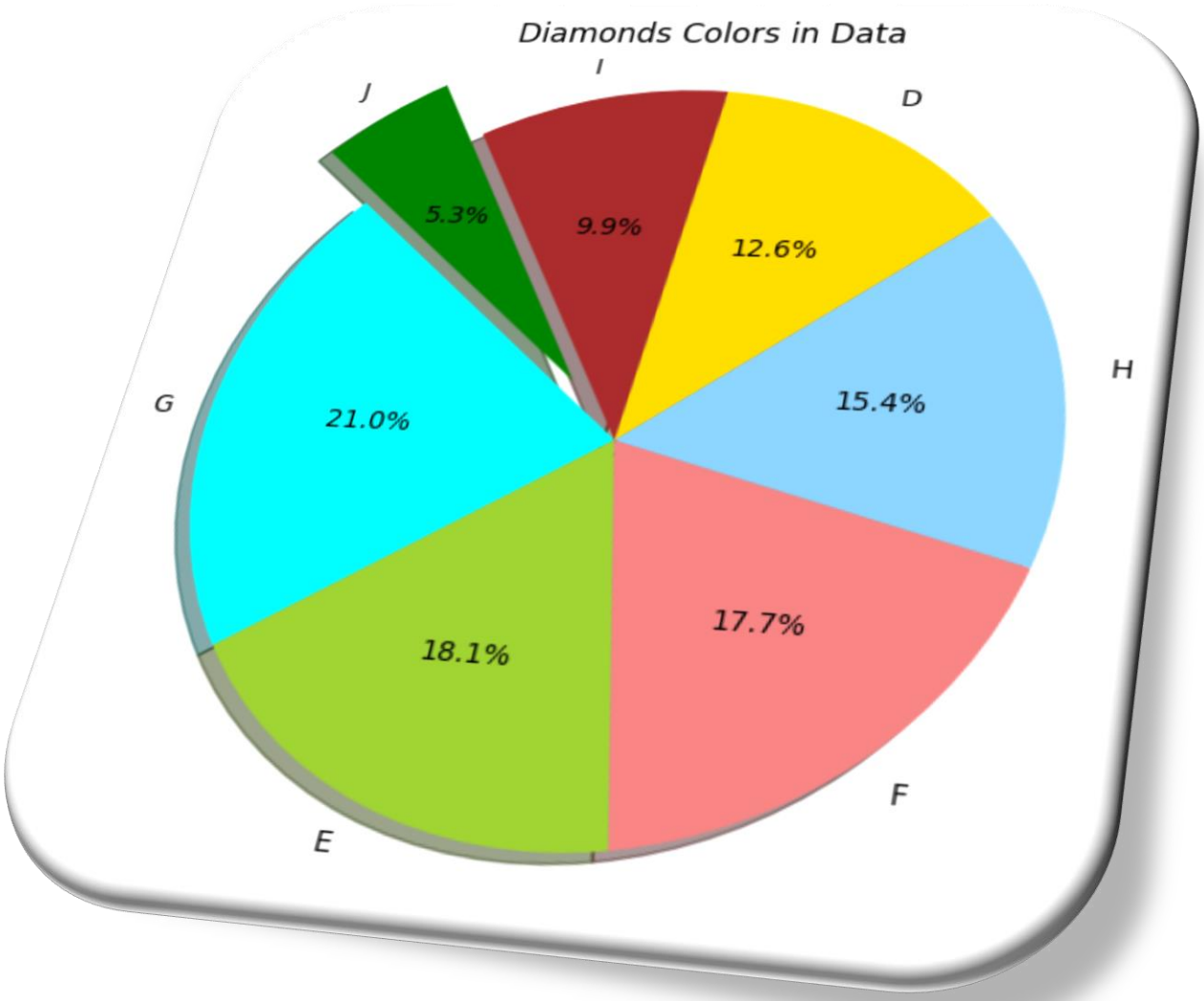
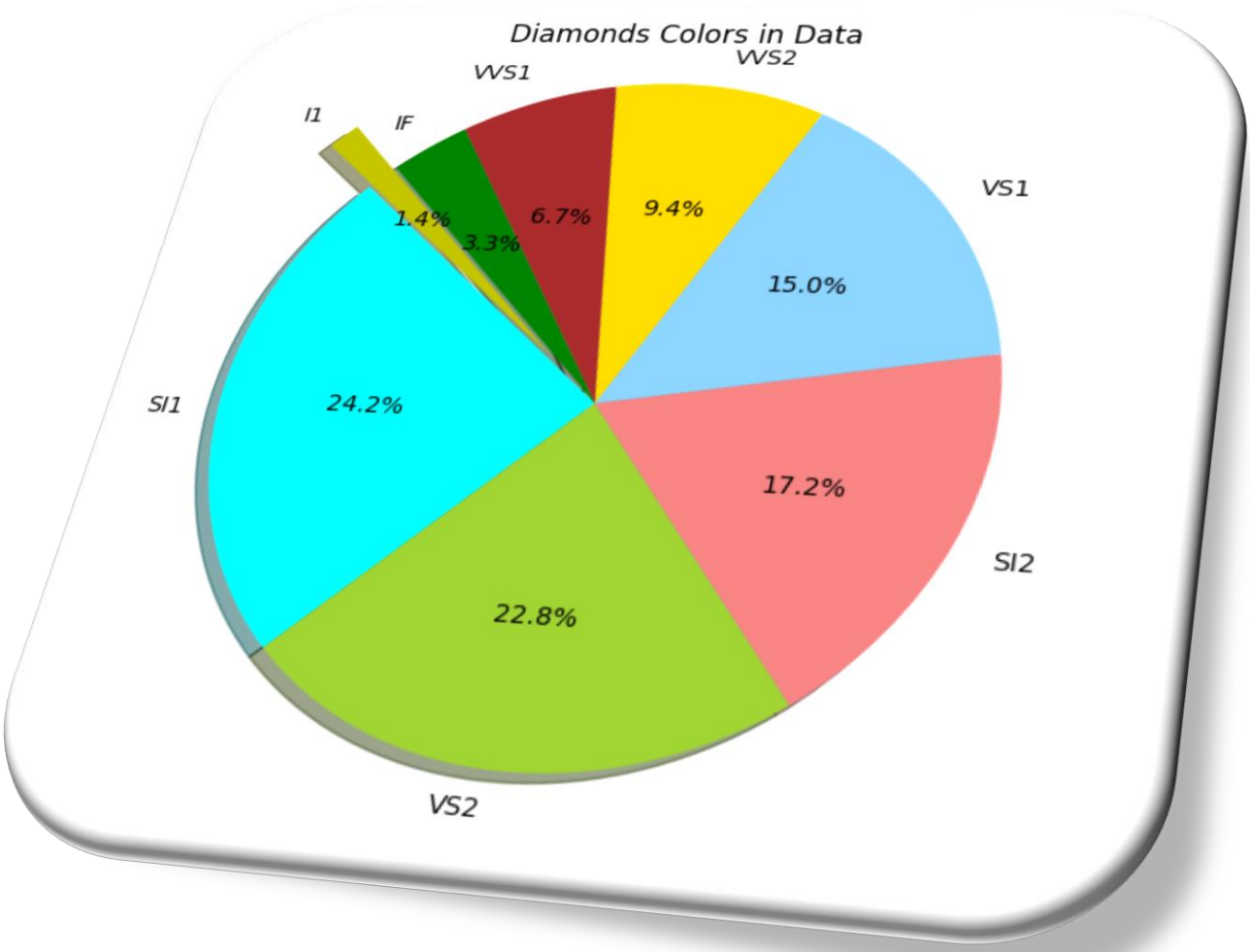
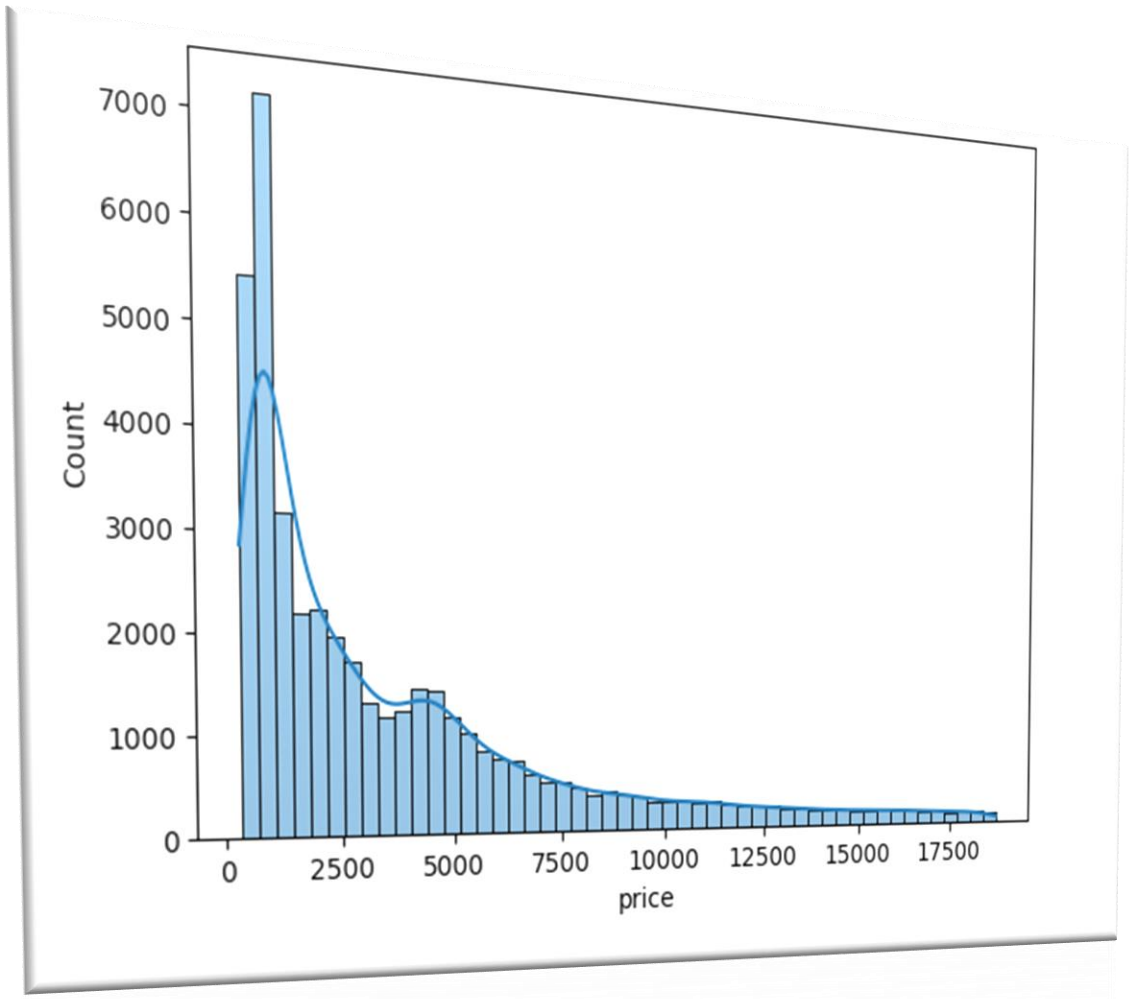
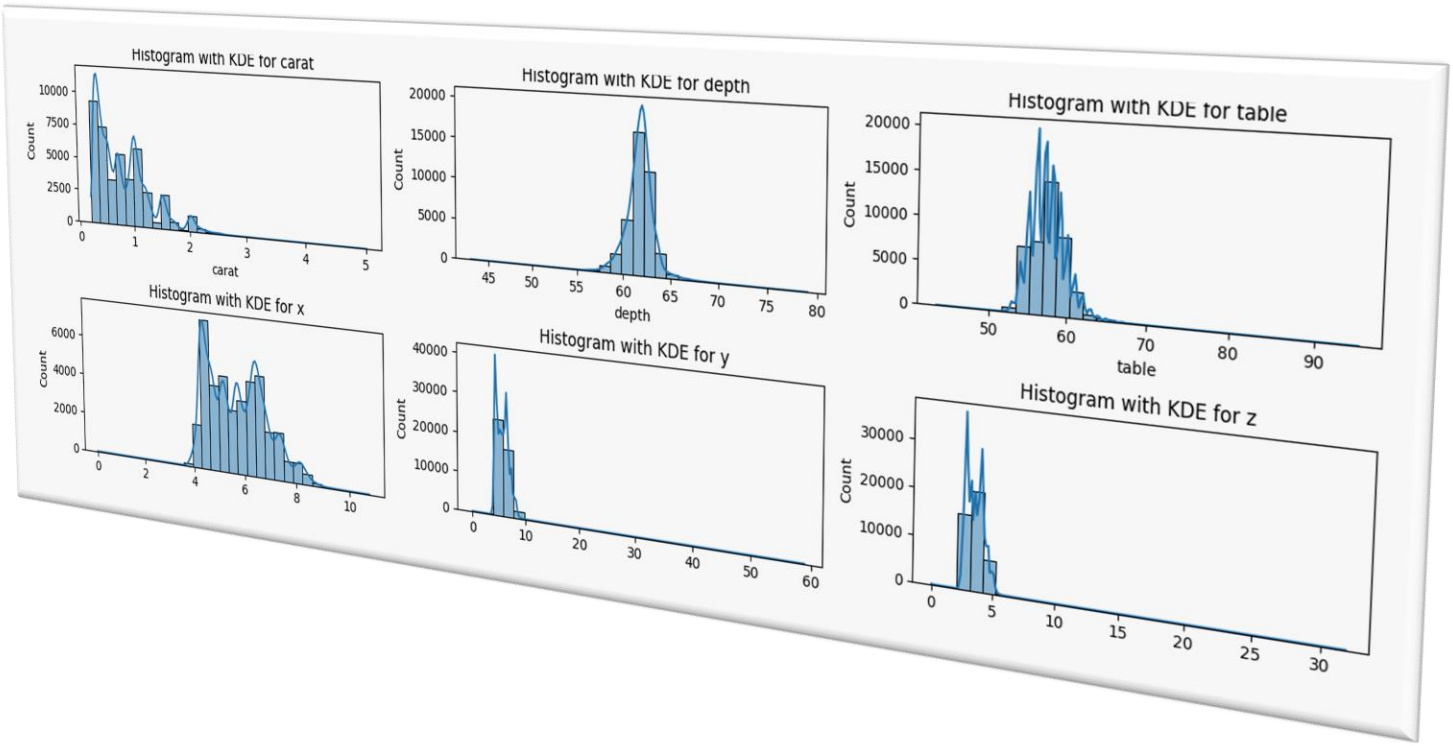
Looking at the big picture of the data

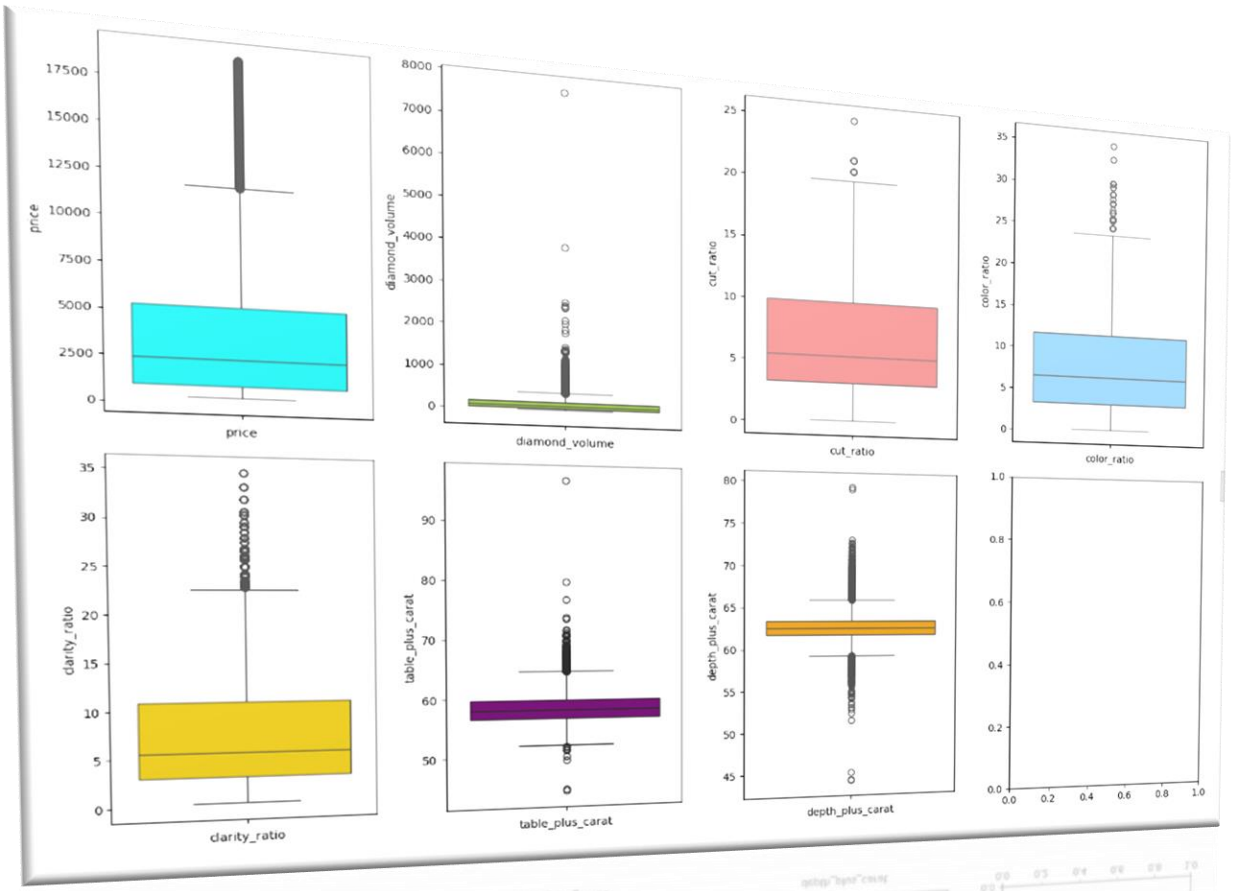



Diamonds Colors in Data
J
I
D
H
G
F
E
5.3%
9.9%
12.6%
15.4%
21.0%
17.7%
18.1%


Diamonds Colors in Data
VVS1
VVS2
I1
IF
VS1
1.4%
6.7%
9.4%
3.3%
15.0%
SI1
24.2%
17.2%
SI2
22.8%
VS2


7000
6000
5000
4000
3000
2000
1000
0
Count
0
2500
5000
7500
10000
12500
15000
17500
price


Histogram with KDE for carat
Count
carat
Histogram with KDE for depth
Count
depth
Histogram with KDE for table
Count
table
Histogram with KDE for x
Count
Histogram with KDE for y
Count
Histogram with KDE for z
Count


price
diamond_volume
cut_ratio
color_ratio
clarity_ratio
table_plus_carat
depth_plus_carat


Correlation Matrix
cut
color
clarity
depth
table
price
x
y
z
1.00 -0.14 -0.29 -0.35 0.02 0.18 0.92 0.98 0.95 0.95
-0.14 1.00 0.02 0.19 -0.22 -0.43 -0.06 -0.13 -0.12 -0.15
-0.29 0.02 1.00 -0.03 -0.05 -0.02 -0.17 -0.27 -0.26 -0.27
-0.35 0.19 -0.03 1.00 -0.06 -0.16 -0.15 -0.37 -0.36 -0.37
0.02 -0.22 -0.05 -0.06 1.00 -0.30 -0.01 -0.03 -0.03 0.09
0.18 -0.43 -0.02 -0.16 -0.30 1.00 0.13 0.20 0.18 0.15
0.92 -0.06 -0.17 -0.15 -0.01 0.13 1.00 0.89 0.86 0.86
0.98 -0.13 -0.27 -0.37 -0.03 0.20 0.89 1.00 0.97 0.97
0.95 -0.12 -0.26 -0.36 -0.03 0.18 0.86 0.97 1.00 0.94
0.95 -0.15 -0.27 -0.37 0.09 0.15 0.86 0.97 0.94 1.00
0.8
0.6
0.4
0.2
0.0
−0.2

From this big picture, we have noticed that:

- **Categorical data are not balanced.**
    - We determine specific percentages and apply oversampling to features that exist in a low percentage, and undersampling to features that exist in a high percentage, to ensure that they all exist in the same percentage.

- **The target value, price, is highly left-skewed.**
    - We apply the logarithmic scale to ensure that the data is normalized and to reduce the range of prices.

- **Some features are highly skewed and have different ranges.**
    - We apply the logarithmic scale, as we did with the price feature, and also normalize the data.

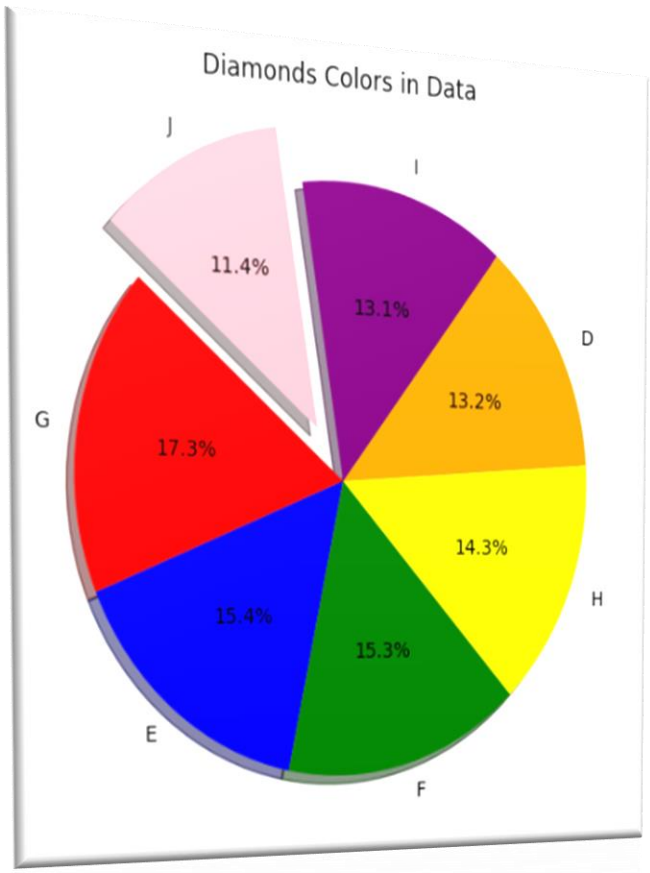
- **The features contain high values of outliers.**
    - We can remove the outliers because they greatly influence the model's ability to predict values within a certain range. Instead, we use the logarithmic scale to small range and reduce outliers.

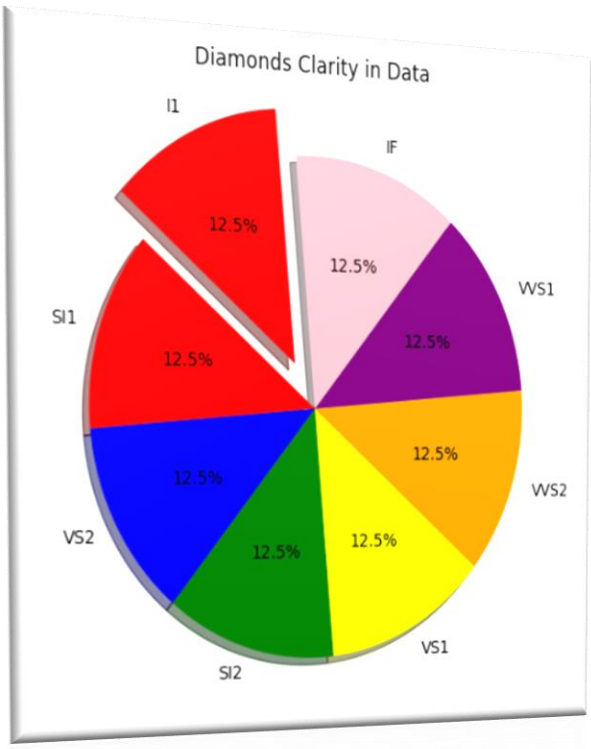
- **X, Y, Z, and carat features are highly correlated with the price.**
    - We create new features from these existing features and do not remove them, even though they are highly correlated. Removing them reduces the model's accuracy.

- **Data doesn’t have many features correlated to the price.**
    - We created three new features.

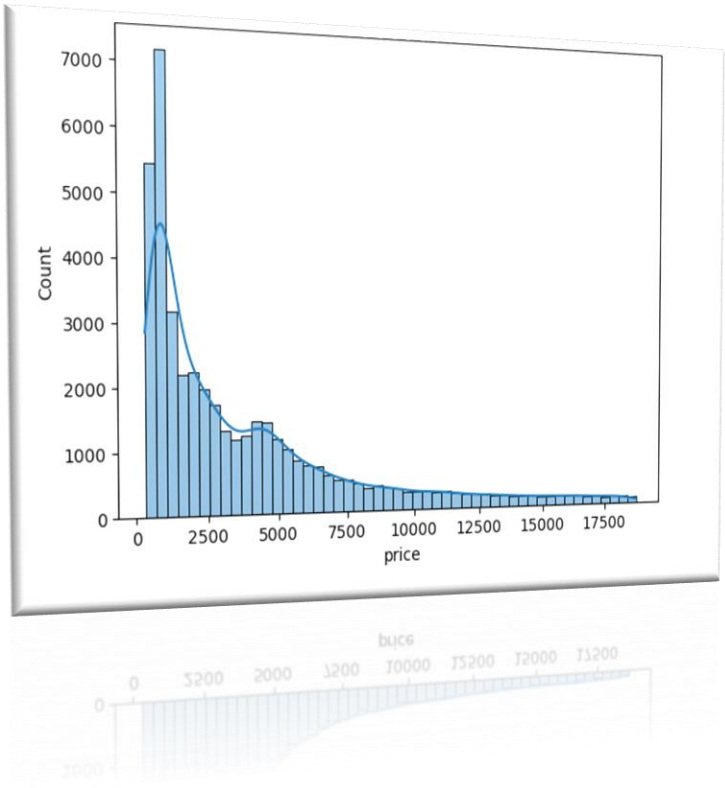
First thing we create new features correlated to the price and remove cut and depth which are not correlated to the price:

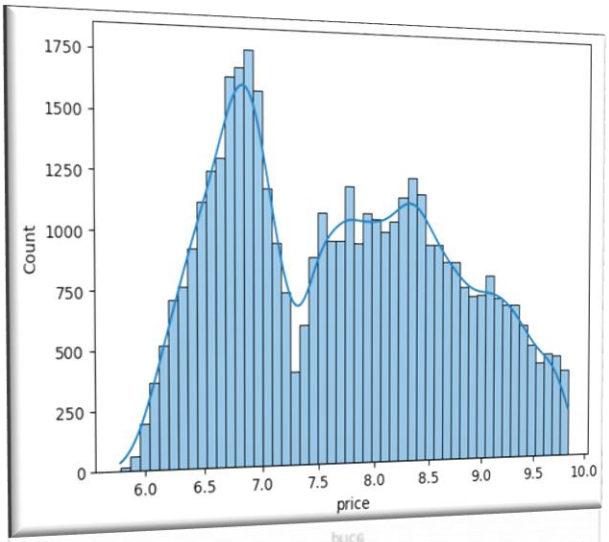
We have applying oversampling and undersampling to the categorical feature:



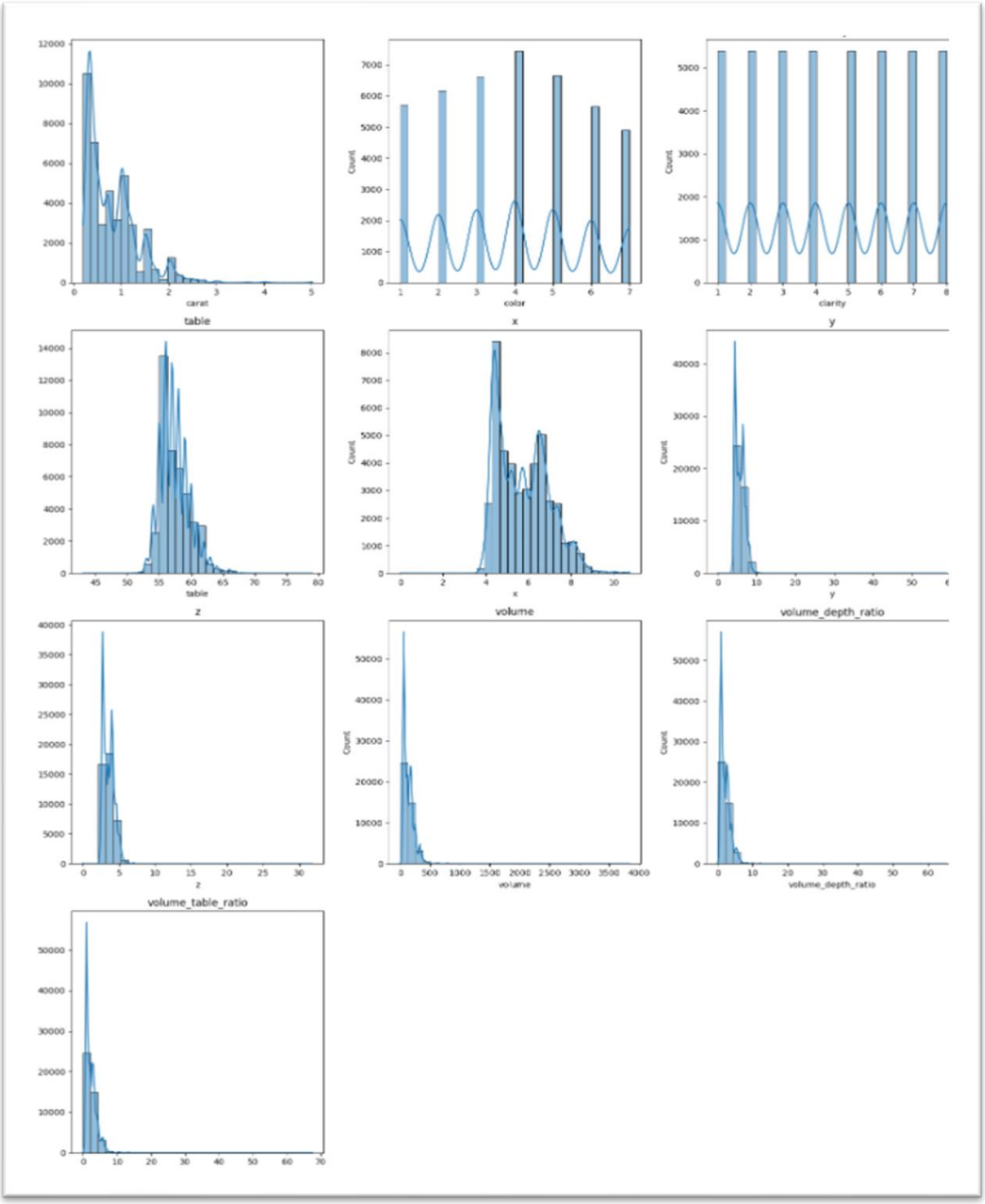


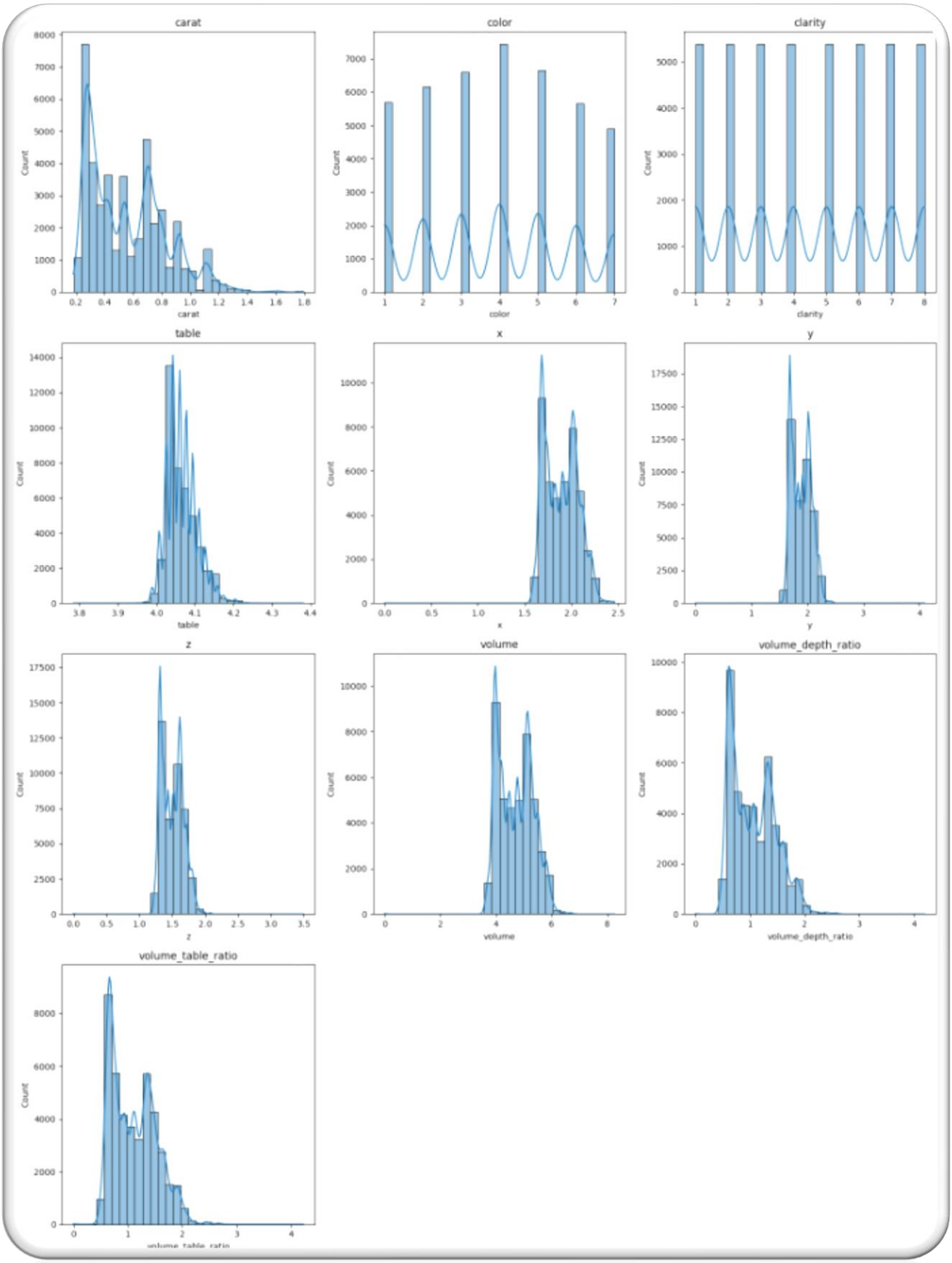
We have applied a logarithmic scale to the prices to address the issue of highly left-skewed data and to reduce the range and solve the problem of outliers:





We applied a logarithmic scale to address the left-skewed distribution of the carat feature and to narrow the range of all features, thereby addressing the issue of outliers. Subsequently, we performed normalization on the features to ensure a smaller scale and a mean of zero:




carat
color
clarity
table
x
y
z
volume
volume_depth_ratio
volume_table_ratio
Count

	carat	table	x	y	z	volume	volume_depth_ratio	volume_table_ratio	price
count	4.312800e+04	4.312800e+04	4.312800e+04	4.312800e+04	4.312800e+04	4.312800e+04	4.312800e+04	4.312800e+04	43128.000000
mean	-1.370737e-16	-1.948028e-15	1.133494e-15	-9.542440e-16	-5.588390e-16	6.010156e-16	4.323094e-16	1.212575e-16	7.745299
std	1.000012e+00	1.000012e+00	1.000012e+00	1.000012e+00	1.000012e+00	1.000012e+00	1.000012e+00	1.000012e+00	1.001382
min	-1.411102e+00	-7.315294e+00	-1.070661e+01	-1.081159e+01	-9.078761e+00	-7.593446e+00	-2.648100e+00	-2.722815e+00	5.789960
25%	-9.189991e-01	-6.142355e-01	-9.352538e-01	-9.351735e-01	-9.329006e-01	-9.314457e-01	-9.301276e-01	-9.382759e-01	6.852243
50%	-1.173909e-01	-1.640217e-01	2.321928e-02	3.103315e-02	3.656647e-02	5.378109e-02	-6.271268e-02	-6.648548e-02	7.723562
75%	6.497424e-01	7.135756e-01	7.835498e-01	7.827099e-01	7.423372e-01	7.716198e-01	7.407497e-01	7.351745e-01	8.530307
max	4.572998e+00	8.160699e+00	3.220093e+00	1.255471e+01	1.201249e+01	5.712088e+00	7.777952e+00	7.625078e+00	9.841399

- **It is important to have features with zero mean before training the model.**

- After the data is prepared for training, we trained it using AutoGluon, utilizing RMSE as the evaluation metric. The training process took approximately one hour to select the best model and optimal hyperparameters.

- When training the model on 80% of the data and testing it on 20% of it we get:

    - Accuracy:

    - RMSE:

- The model final score on Kaggle is: