Importing Intel Library

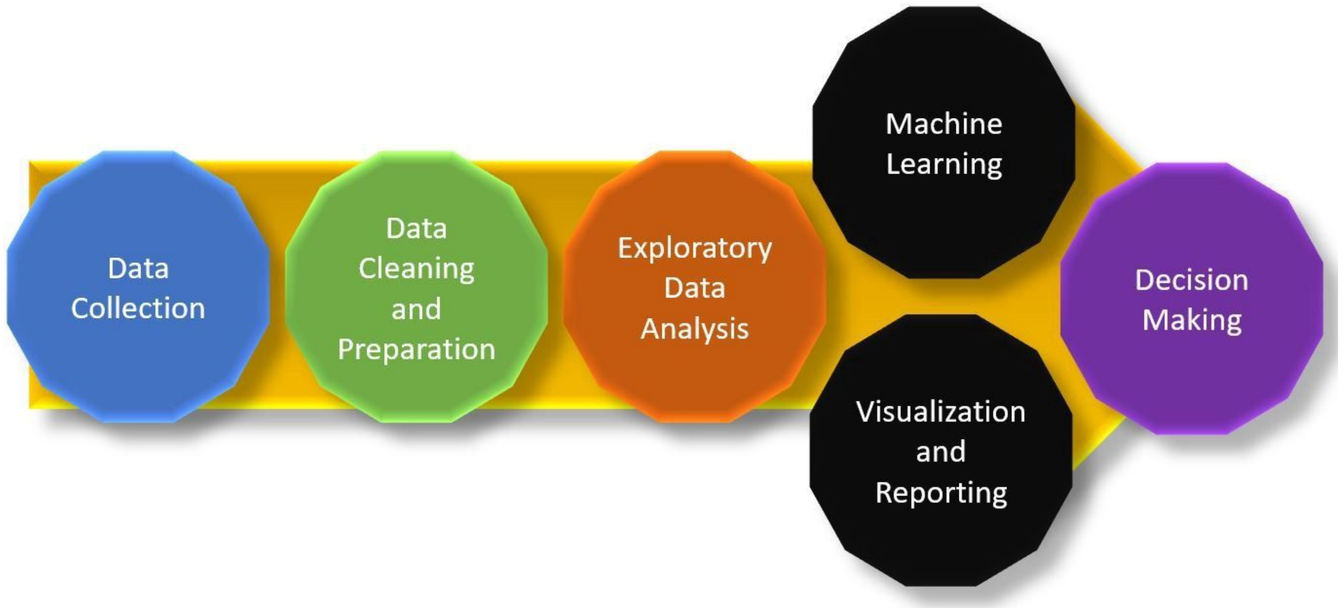
- We are running this intel patch in the begining so all the sklearn libraries imported will have intel extension for faster processing

In [4]:
```python
from sklearnex import patch_sklearn
patch_sklearn()
```

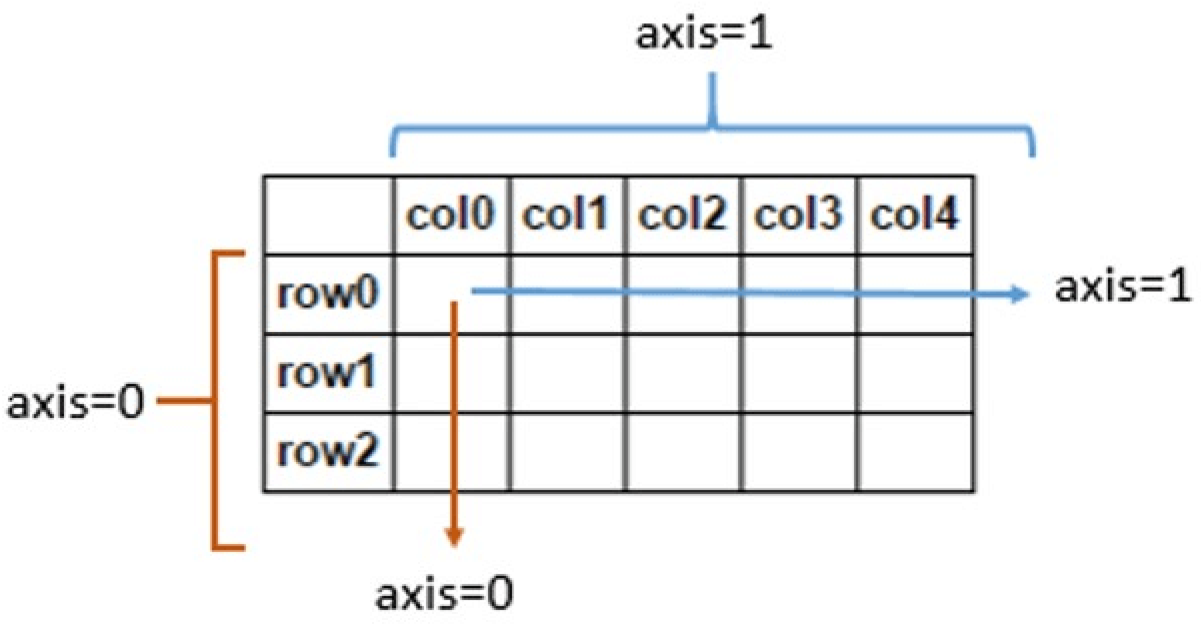
```
Intel(R) Extension for Scikit-learn* enabled (https://github.com/intel/scikit-learn-in
telex)
```

Importing All the Libraries

In [5]:
```python
import pandas as pd
import numpy as np
from numpy import mean
from numpy import std
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import f1_score
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import xgboost
from sklearn import ensemble
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from catboost import CatBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
```


Data Collection
Data Cleaning and Preparation
Exploratory Data Analysis
Machine Learning
Visualization and Reporting
Decision Making

Loading the Dataset



In [6]:
```python
data = pd.read_csv('dataset.csv', index_col = 0)
```

In [7]:
```python
data.head(5)
```
Out[7]:

Index	pH	Iron	Nitrate	Chloride	Lead	Zinc	Color	Turbidity	Fluoride	Coppe
0	8.332988	0.000083	8.605777	122.799772	3.713298e-52	3.434827	Colorless	0.022683	0.607283	0.14459
1	6.917863	0.000081	3.734167	227.029851	7.849262e-94	1.245317	Faint Yellow	0.019007	0.622874	0.43783
2	5.443762	0.020106	3.816994	230.995630	5.286616e-76	0.528280	Light Yellow	0.319956	0.423423	0.43158
3	7.955339	0.143988	8.224944	178.129940	3.997118e-176	4.027879	Near Colorless	0.166319	0.208454	0.23945
4	8.091909	0.002167	9.925788	186.540872	4.171069e-132	3.807511	Light Yellow	0.004867	0.222912	0.61657

5 rows × 23 columns

Data Cleansing

In [8]:
```python
data.describe()
```
Out[8]:

	pH	Iron	Nitrate	Chloride	Lead	Zinc	Turbidity
count	5.840788e+06	5.917089e+06	5.851117e+06	5.781311e+06	5.929933e+06	5.800716e+06	5.907027e+06
mean	7.445373e+00	1.279027e-01	6.169970e+00	1.842970e+02	1.498336e-03	1.550255e+00	5.215093e-01
std	8.881665e-01	4.799915e-01	3.256667e+00	6.842828e+01	3.250641e-02	1.546368e+00	9.258807e-01
min	1.057113e+00	2.047587e-53	2.861727e-01	2.363919e+01	0.000000e+00	1.482707e-08	1.029712e-16
25%	6.894328e+00	9.992949e-06	3.973078e+00	1.381341e+02	1.500283e-122	4.148202e-01	3.872368e-02
50%	7.449564e+00	2.249640e-03	5.604051e+00	1.760178e+02	2.213625e-62	1.081818e+00	2.097680e-01
75%	8.014424e+00	5.455290e-02	7.672402e+00	2.179811e+02	3.592165e-27	2.230841e+00	6.249132e-01
max	1.291072e+01	1.935315e+01	9.639078e+01	1.507310e+03	5.844281e+00	2.836867e+01	2.371527e+01

In [9]:
```
data.isna().sum()
```

Out[9]:
```
pH                        116054
Iron                       39753
Nitrate                   105725
Chloride                  175531
Lead                       26909
Zinc                      156126
Color                       5739
Turbidity                  49815
Fluoride                  189156
Copper                    199402
Odor                      178891
Sulfate                   197418
Conductivity              163861
Chlorine                   57825
Manganese                 109583
Total Dissolved Solids      1670
Source                     88262
Water Temperature         168233
Air Temperature            29728
Month                      95668
Day                        99603
Time of Day               114519
Target                         0
dtype: int64
```

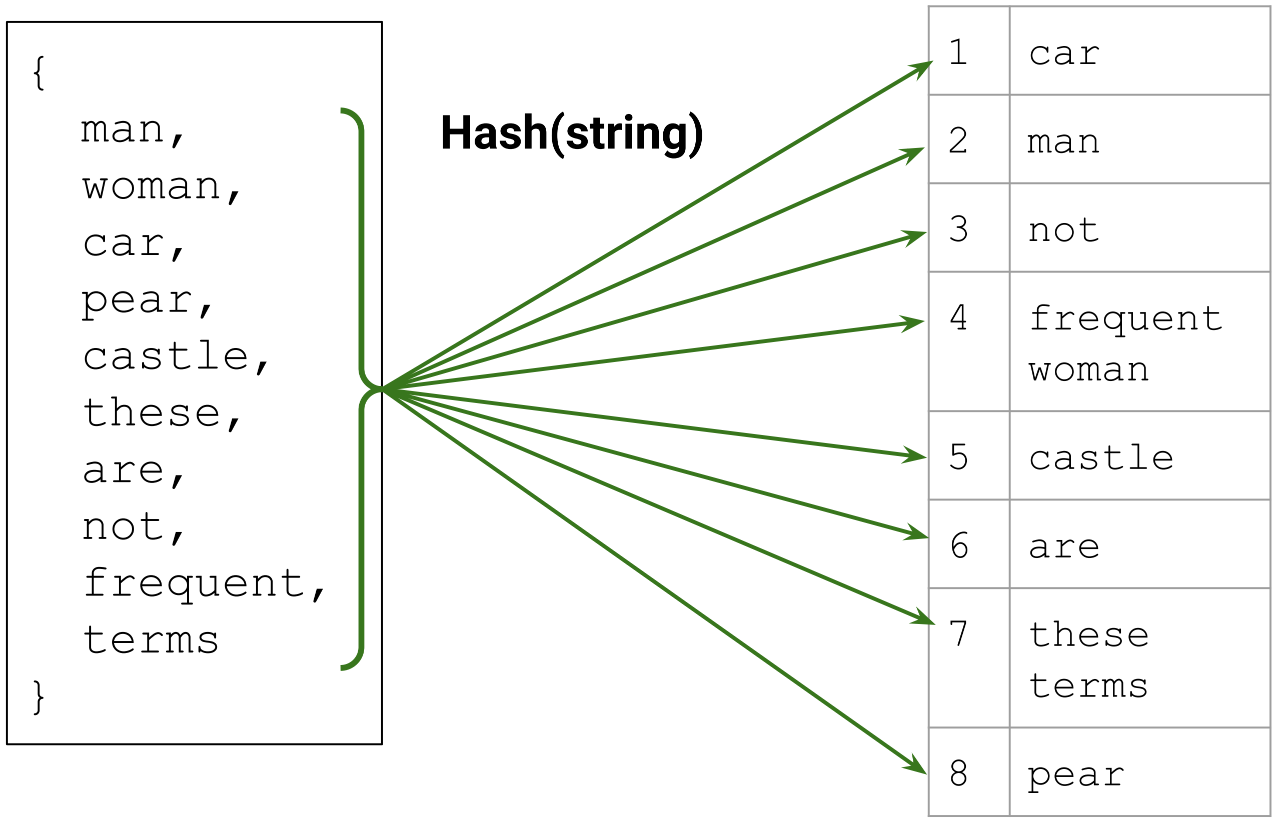
Filling all the Null Values Using Forward Fill Method

- Since there is such high standard deviation in the dataset i.e. the values are spread over wider range. So instead of filling null values by mean of a column we are using forward fill method.

In [10]:
```
data.fillna(method='ffill', inplace=True)
```

Converting all the Columns of String Data Type to Integer Type Using Factorization Method

- We are converting all the categorical columns into numerical data type so we can use it for training our model. Since machine learning model only accepts numerical values.



```
In [11]:
df_numeric = data.select_dtypes(exclude=['object'])
df_obj = data.select_dtypes(include=['object']).copy()

for c in df_obj:
    df_obj[c] = pd.factorize(df_obj[c])[0]

data = pd.concat([df_obj,df_numeric], axis=1)
```

Correlation Matrix

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

Where,

r = Pearson Correlation Coefficient

x_i = x variable samples y_i = y variable sample

$\bar{x}$ = mean of values in x variable $\bar{y}$ =mean of values in y variable

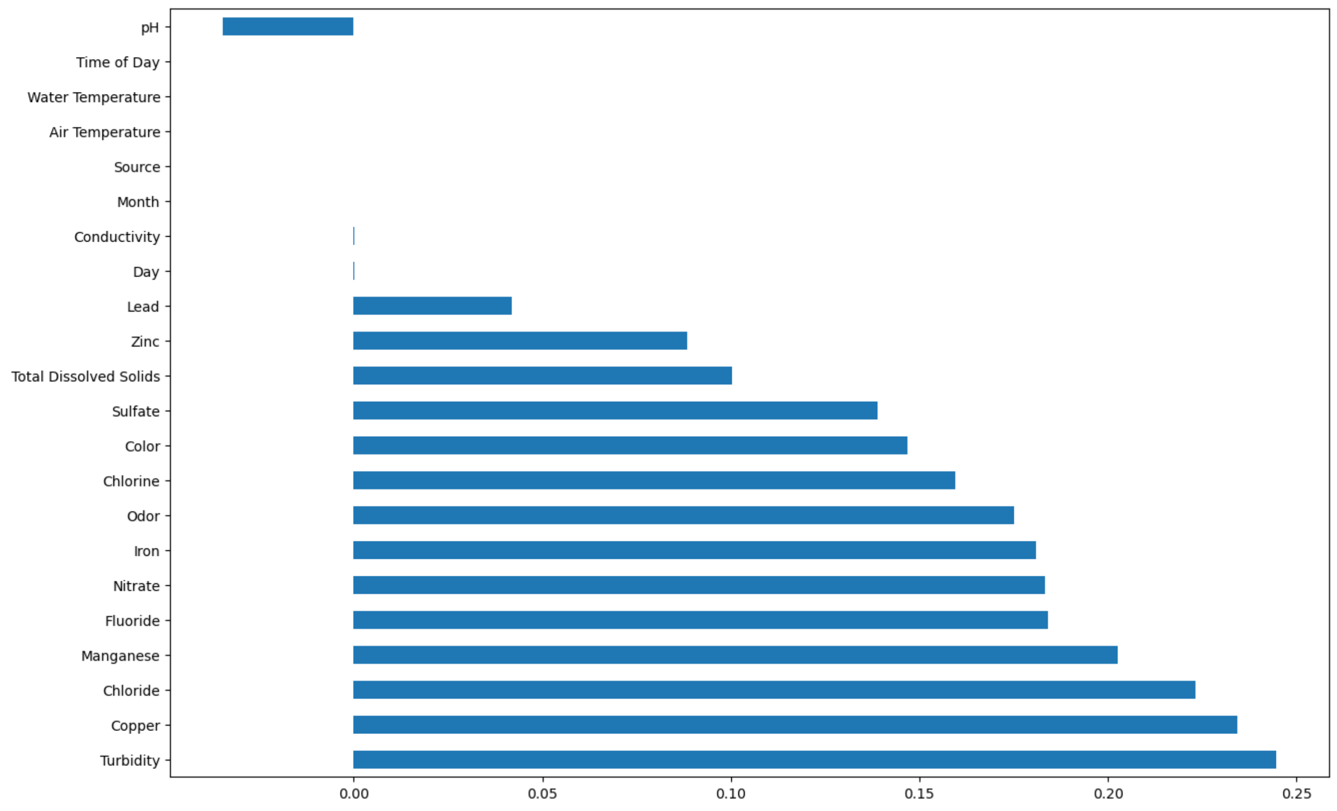
In [12]:
```python
data.corr(method='pearson').style.format("{:.3}").background_gradient(cmap=plt.get_
```
Out[12]:

	Color	Source	Month	pH	Iron	Nitrate	Chloride	Lead	Zinc
Color	1.0	0.000479	-0.000313	-0.00791	0.0425	0.0417	0.0514	0.00984	0.0205
Source	0.000479	1.0	-1.23e-05	0.000656	0.000114	0.000529	0.000452	0.000471	2.02e-05
Month	-0.000313	-1.23e-05	1.0	-0.000285	-0.000142	0.000123	8.18e-05	0.00021	-0.000125
pH	-0.00791	0.000656	-0.000285	1.0	-0.00978	-0.00946	-0.0124	-0.00232	-0.00502
Iron	0.0425	0.000114	-0.000142	-0.00978	1.0	0.0516	0.0637	0.0109	0.0252
Nitrate	0.0417	0.000529	0.000123	-0.00946	0.0516	1.0	0.0637	0.0114	0.0249
Chloride	0.0514	0.000452	8.18e-05	-0.0124	0.0637	0.0637	1.0	0.0139	0.0303
Lead	0.00984	0.000471	0.00021	-0.00232	0.0109	0.0114	0.0139	1.0	0.00582
Zinc	0.0205	2.02e-05	-0.000125	-0.00502	0.0252	0.0249	0.0303	0.00582	1.0
Turbidity	0.0564	-0.000231	-0.000425	-0.0136	0.0694	0.0703	0.0854	0.0165	0.0338
Fluoride	0.0422	0.000387	0.000147	-0.0101	0.0519	0.052	0.0636	0.0131	0.0243
Copper	0.0535	0.000304	0.000215	-0.0133	0.0673	0.0666	0.0808	0.0153	0.0323
Odor	0.0406	-0.000173	0.000335	-0.0094	0.0497	0.0494	0.0613	0.0113	0.0245
Sulfate	0.0316	-0.000307	0.000173	-0.00713	0.0404	0.0392	0.0477	0.00912	0.0192
Conductivity	-4.98e-05	6.98e-05	0.000414	0.000353	0.000269	0.000164	-0.000539	-0.000103	-3.83e-05
Chlorine	0.0369	0.000541	0.000908	-0.00774	0.045	0.0452	0.055	0.0105	0.0217
Manganese	0.0465	-0.000126	-0.000388	-0.0111	0.0588	0.0581	0.0701	0.0135	0.0272
Total Dissolved Solids	0.0233	0.000459	-0.000138	-0.00522	0.0284	0.029	0.036	0.00585	0.0138
Water Temperature	-0.000909	-0.000106	0.000282	-0.000399	0.000868	-0.00013	-0.000325	-0.000107	-0.000402
Air Temperature	-0.000538	0.000491	0.000392	0.000521	-0.000391	0.000261	-0.000247	-0.000485	2.85e-05
Day	0.000675	0.000393	-0.00596	0.000843	-9.22e-05	-6.66e-05	0.000135	0.000188	0.000218
Time of Day	-6.49e-06	0.000362	0.000222	-0.000113	0.000339	-4.43e-05	-0.000273	0.000586	0.000659
Target	0.147	-4.74e-05	-3.96e-05	-0.0347	0.181	0.183	0.223	0.042	0.0884

In [13]:
```python
df_correlation = data.corr()
```

In [14]:
```python
plt.rcParams['figure.figsize'] = [15, 10]
(df_correlation
     .Target
     .drop('Target')
     .sort_values(ascending=False)
     .plot
     .barh())
```

Out[14]:
```
<AxesSubplot:>
```



In [15]:
```python
data.corr()['Target'].sort_values()
```

Out[15]:
```
pH                       -0.034737
Time of Day              -0.000232
Water Temperature        -0.000113
Air Temperature          -0.000048
Source                   -0.000047
Month                    -0.000040
Conductivity              0.000078
Day                       0.000241
Lead                      0.042007
Zinc                      0.088429
Total Dissolved Solids    0.100231
Sulfate                   0.138839
Color                     0.146770
Chlorine                  0.159533
Odor                      0.175152
Iron                      0.180897
Nitrate                   0.183399
Fluoride                  0.184089
Manganese                 0.202702
Chloride                  0.223133
Copper                    0.234398
Turbidity                 0.244534
Target                    1.000000
Name: Target, dtype: float64
```

In [16]:
```python
cor = data.corr()['Target'].sort_values()
```

In [17]:
```python
df = data.copy()
```

Removing all the Columns from the Dataset whose Correlation Value is Less than 0.01 with the Target Column

- Since columns with such low correlation with not be useful for predicting the target column. So we will be dropping through column while training the predictive model

In [18]:
```python
arr = []
for k, v in cor.items():
    if abs(v) < 0.01:
        arr.append(k)
```

In [19]:
```python
df = df.drop(arr, axis=1)
```

In [20]:

```python
df.head(5)
```

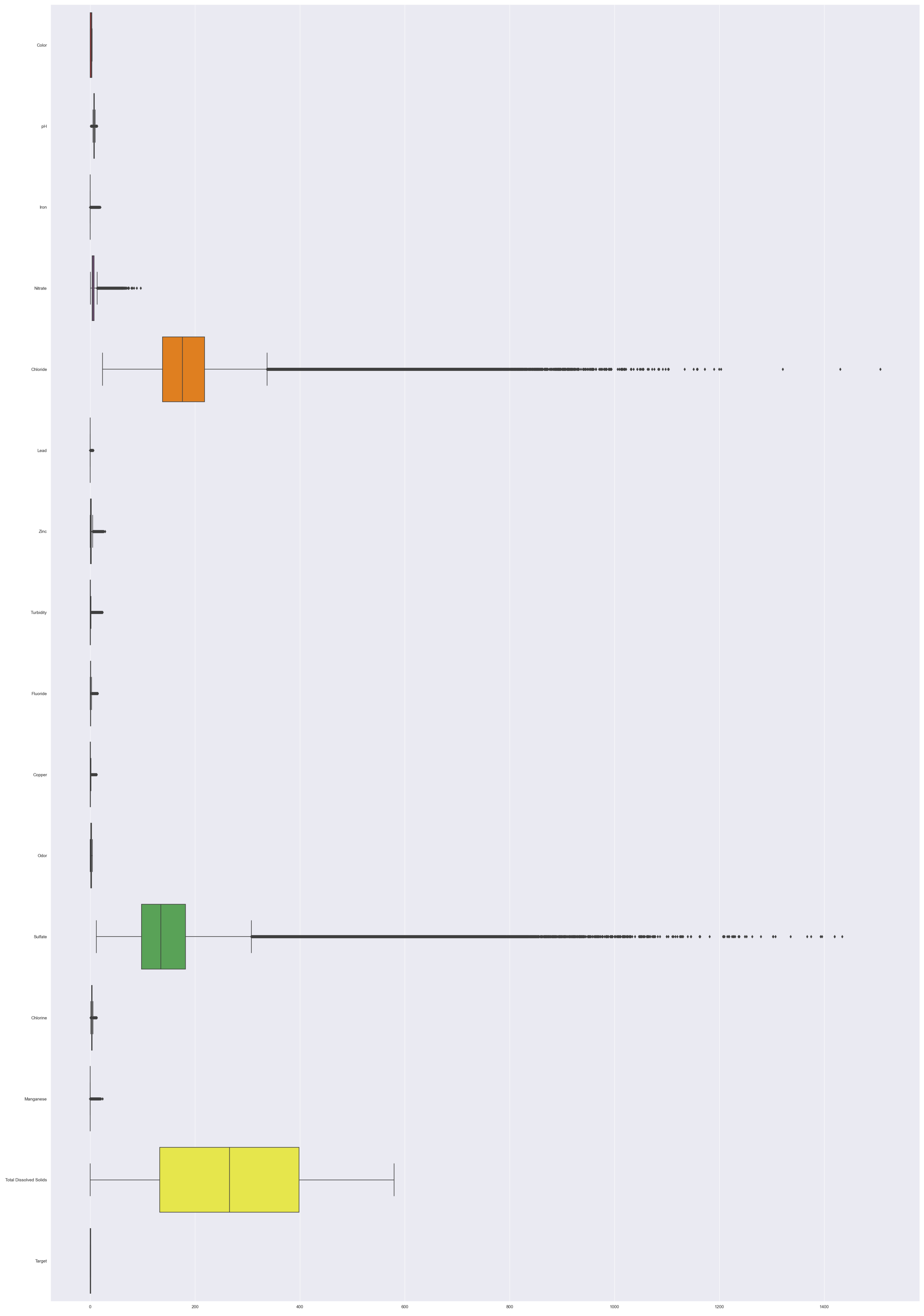
Out[20]:

	Color	pH	Iron	Nitrate	Chloride	Lead	Zinc	Turbidity	Fluoride	Copper
Index										
0	0	8.332988	0.000083	8.605777	122.799772	3.713298e-52	3.434827	0.022683	0.607283	0.144599
1	1	6.917863	0.000081	3.734167	227.029851	7.849262e-94	1.245317	0.019007	0.622874	0.437835
2	2	5.443762	0.020106	3.816994	230.995630	5.286616e-76	0.528280	0.319956	0.423423	0.431588
3	3	7.955339	0.143988	8.224944	178.129940	3.997118e-176	4.027879	0.166319	0.208454	0.239451
4	2	8.091909	0.002167	9.925788	186.540872	4.171069e-132	3.807511	0.004867	0.222912	0.616574

BoxPlot (Pictorial View of all the Outliers in the Data)

In [21]:
```
sns.set(rc={'figure.figsize':(40,60)})
sns.boxplot(data=df, orient="h", palette="Set1")
```

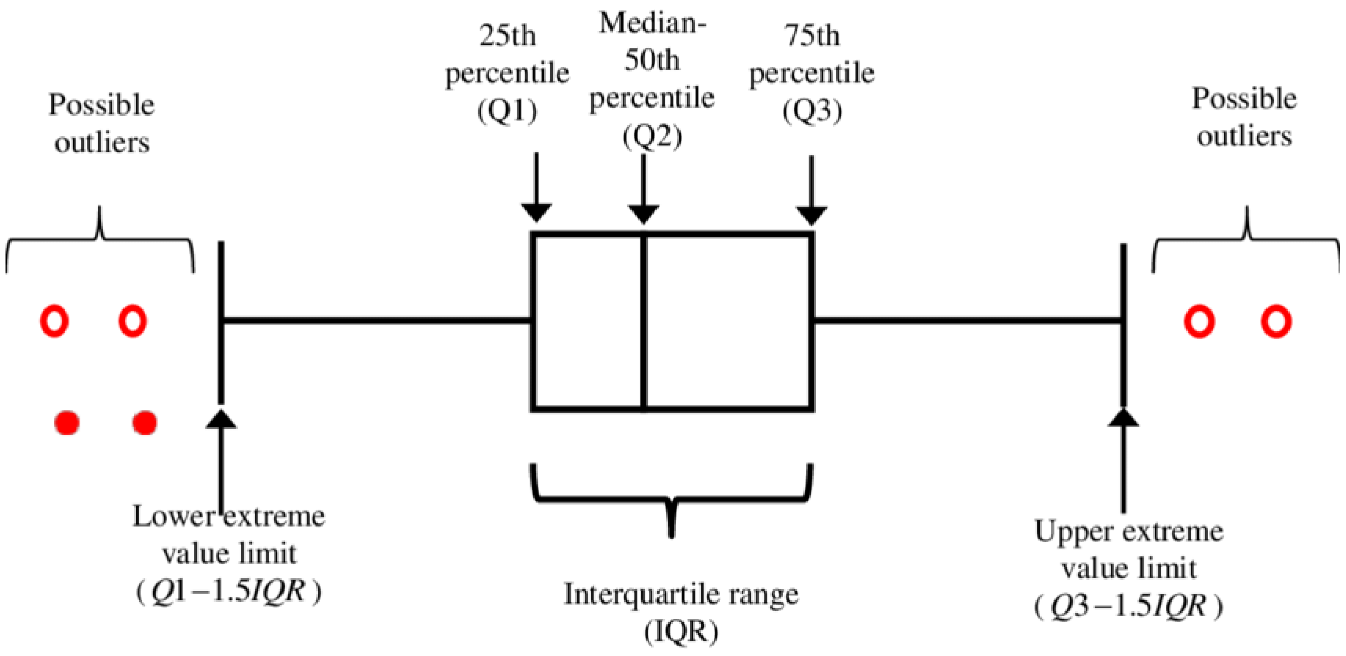
Out[21]:
```
<AxesSubplot:>
```



Color
pH
Iron
Nitrate
Chloride
Lead
Zinc
Turbidity
Fluoride
Copper
Odor
Sulfate
Chlorine
Manganese
Total Dissolved Solids
Target
0
200
400
600
800
1000
1200
1400

Removing all the Outliers from the Dataset

- Since outliers can skew the results of the predictive model. It is better to remove those from the dataset.



25th percentile (Q1)
Median- 50th percentile (Q2)
75th percentile (Q3)
Possible outliers
Possible outliers
Lower extreme value limit ($Q1-1.5IQR$)
Interquartile range (IQR)
Upper extreme value limit ($Q3-1.5IQR$)

In [22]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
```

In [23]:
```
((df < (Q1 - 1.5 * IQR)) | (df > (Q3 + 1.5 * IQR))).sum()
```

Out[23]:
```
Color                          0
pH                        157706
Iron                      955610
Nitrate                   196950
Chloride                  193937
Lead                     1468591
Zinc                      184256
Turbidity                 464338
Fluoride                  207346
Copper                    318721
Odor                           0
Sulfate                   151300
Chlorine                  101584
Manganese                 954536
Total Dissolved Solids         0
Target                         0
dtype: int64
```

In [24]:
```
df = df[~((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)]
df.shape
```

Out[24]:
```
(2698298, 16)
```

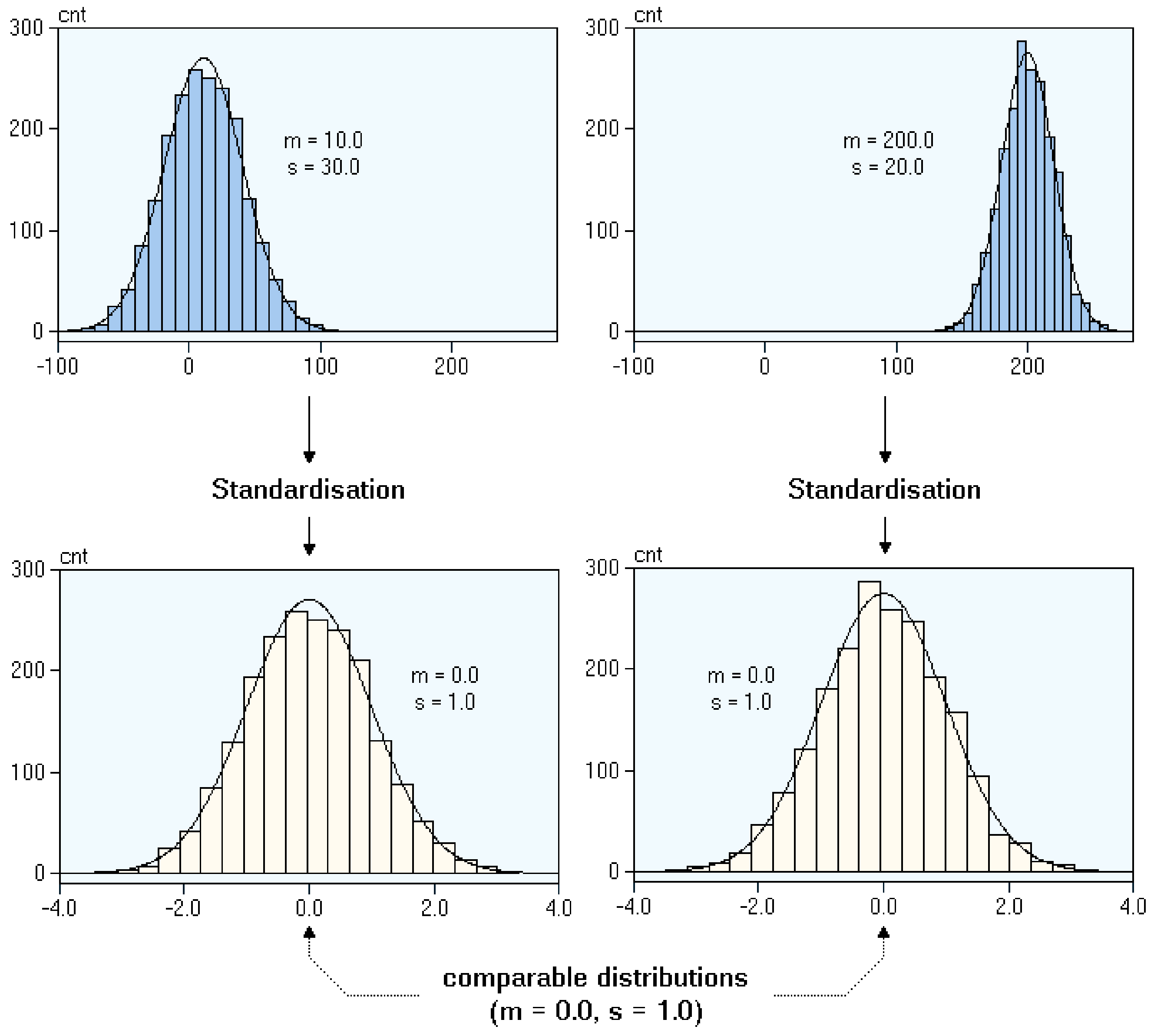
In [25]:
```
data.shape
```
Out[25]:
```
(5956842, 23)
```
In [26]:
```
df.head(5)
```
Out[26]:

	Color	pH	Iron	Nitrate	Chloride	Lead	Zinc	Turbidity	Fluoride	Copper
Index										
0	0	8.332988	8.347252e-05	8.605777	122.799772	3.713298e-52	3.434827	0.022683	0.607283	0.144599
1	1	6.917863	8.053827e-05	3.734167	227.029851	7.849262e-94	1.245317	0.019007	0.622874	0.437835
4	2	8.091909	2.167128e-03	9.925788	186.540872	4.171069e-132	3.807511	0.004867	0.222912	0.616574
6	2	8.132455	5.526229e-02	4.288010	94.993978	2.919909e-52	1.770221	0.021703	1.111893	0.247116
7	0	7.258203	6.107130e-09	9.261676	182.242341	4.399852e-224	0.416478	0.047803	1.016196	0.298093

In [27]:
```
x = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

Standardizing all The Columns which will be used for Training the Model

- Strandardizing the columns so some of the machine learning model which assign weights to each column while training should not provide higher weight to a column just based on the magnitude of their value.



In [28]:
```
sc_X = StandardScaler()
x = sc_X.fit_transform(x)
```

In [29]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_s
```

Linear Regression

In [30]:
```
regressor = LogisticRegression()
regressor.fit(x_train, y_train)
```

Out[30]:
```
LogisticRegression()
```

In [31]:
```
pred = regressor.predict(x_test)
```

In [32]:
```
accuracy = regressor.score(x_test, y_test)
print(f'Accuracy of Logistic Regression Model is {round(accuracy * 100, 2)} %')
```

```
Accuracy of Logistic Regression Model is 90.47 %
```

XG Boost

In [33]:
```
model = XGBClassifier()
```

In [34]:
```
model.fit(x_train, y_train)
```

Out[34]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In [35]:
```
pred = model.predict(x_test)
```

In [36]:
```
accuracy_xgb = model.score(x_test, y_test)
print(f'Accuracy of XG Boost Model is {round(accuracy_xgb * 100, 4)} %')
```

```
Accuracy of XG Boost Model is 94.7163 %
```

Light GBM

In [37]:
```
model_lgbm = LGBMClassifier()
```

In [38]:
```
model_lgbm.fit(x_train, y_train)
```

Out[38]:
```
LGBMClassifier()
```

In [39]:
```
pred_new = model_lgbm.predict(x_test)
```

In [40]:
```
accuracy_lgbm = model_lgbm.score(x_test, y_test)
print(f'Accuracy of Light Gradient Boost Model is {round(accuracy_lgbm * 100, 4)} %
```
```
Accuracy of Light Gradient Boost Model is 95.003 %
```

CAT Boost

In [41]:
```
model_cat = CatBoostClassifier(verbose=0, n_estimators=100)
```

In [42]:
```
model_cat.fit(x_train, y_train)
```

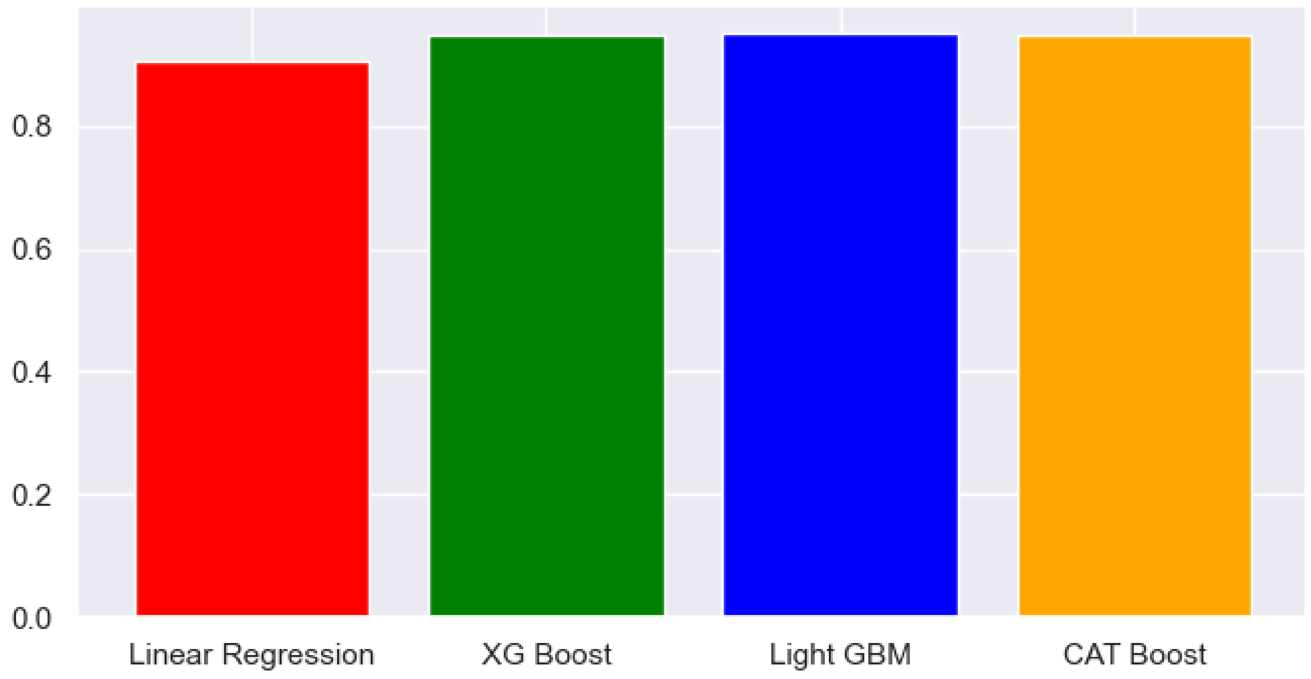
Out[42]:
```
<catboost.core.CatBoostClassifier at 0x1c113dfe100>
```

In [43]:
```
predictions = model_cat.predict(x_test)
```

In [44]:
```
accuracy_cbm = model_cat.score(x_test, y_test)
print(f'Accuracy of Light Gradient Boost Model is {round(accuracy_cbm * 100, 4)} %'
```
```
Accuracy of Light Gradient Boost Model is 94.7898 %
```

Light GBM is giving the best accuracy amongst all the models

In [51]:
```
x = ['Linear Regression', 'XG Boost', 'Light GBM', 'CAT Boost']
y = [accuracy, accuracy_xgb, accuracy_lgbm, accuracy_cbm]
colors = ['red', 'green', 'blue', 'orange']
plt.rcParams['figure.figsize'] = [8,4]
plt.bar(x, y, color=colors)
plt.show()
```



Run Below Four Cells after Running all the Imports to get the Accuracy from the Final Selected Model

In [46]:
```
def preprocessing(dataset_path):

    data = pd.read_csv(dataset_path , index_col = [0])
    data.fillna(method='ffill', inplace=True)

    df_numeric = data.select_dtypes(exclude=['object'])
    df_obj = data.select_dtypes(include=['object']).copy()

    for c in df_obj:
        df_obj[c] = pd.factorize(df_obj[c])[0]

    data = pd.concat([df_obj,df_numeric], axis=1)

    cor = data.corr()['Target'].sort_values()
    df = data.copy()
    arr = []
    for k, v in cor.items():
        if abs(v) < 0.01:
            arr.append(k)
    df = df.drop(arr, axis=1)

    Q1 = df.quantile(0.25)
    Q3 = df.quantile(0.75)
    IQR = Q3 - Q1
    df = df[~((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)]

    x = df.iloc[:, :-1].values
    y = df.iloc[:, -1].values
    sc_X = StandardScaler()
    x = sc_X.fit_transform(x)

    return x, y
```

In [47]:
```
x, y = preprocessing('dataset.csv')
```

In [48]:
```
def training(x, y):

    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, rand
    model = LGBMClassifier()
    model.fit(x_train, y_train)
    pred = model.predict(x_test)
    accuracy = model.score(x_test, y_test)
    f1 = f1_score(y_test, pred)
    return f1, accuracy
```

In [49]:
```
F1, Accuracy = training(x, y)
```

We are able to achieve 95.003 % Accuracy in this problem statement

In [50]:
```python
print(f'Accuracy of the Model is {round(Accuracy * 100, 4)} %')
```

```
Accuracy of the Model is 95.003 %
```