High Level Design (HLD)

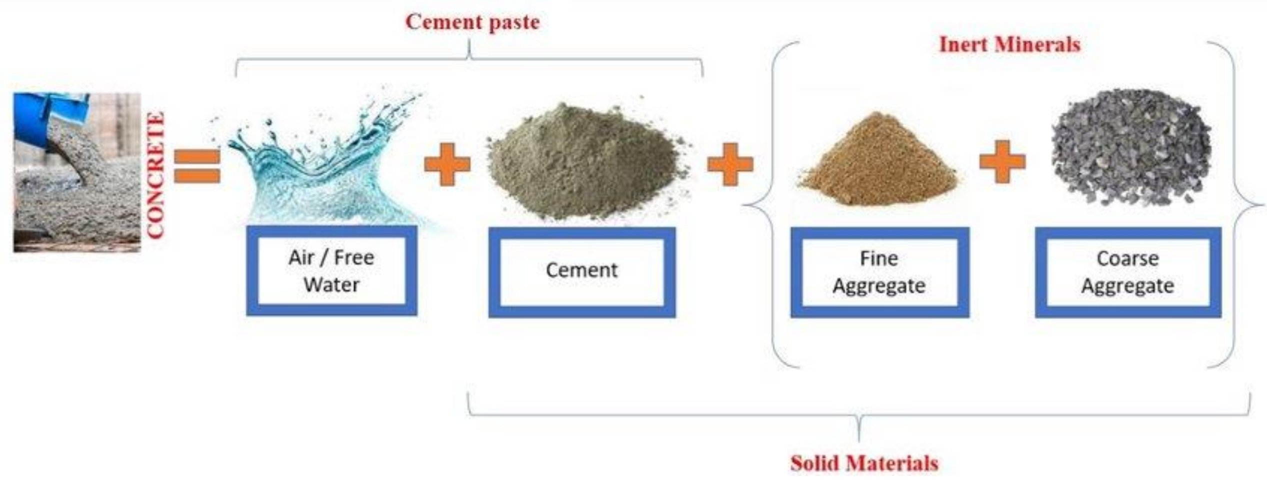
CONCRETE COMPRESSIVE STRENGTH PREDICTION

Project – Machine Learning Technology

Submitted By Paul Praveen

Project Outline

Project Title	**Concrete Compressive Strength Prediction**
Technologies	**Machine Learning Technology**
Domain	**Infra**
Project Difficulties level	**Intermediate**



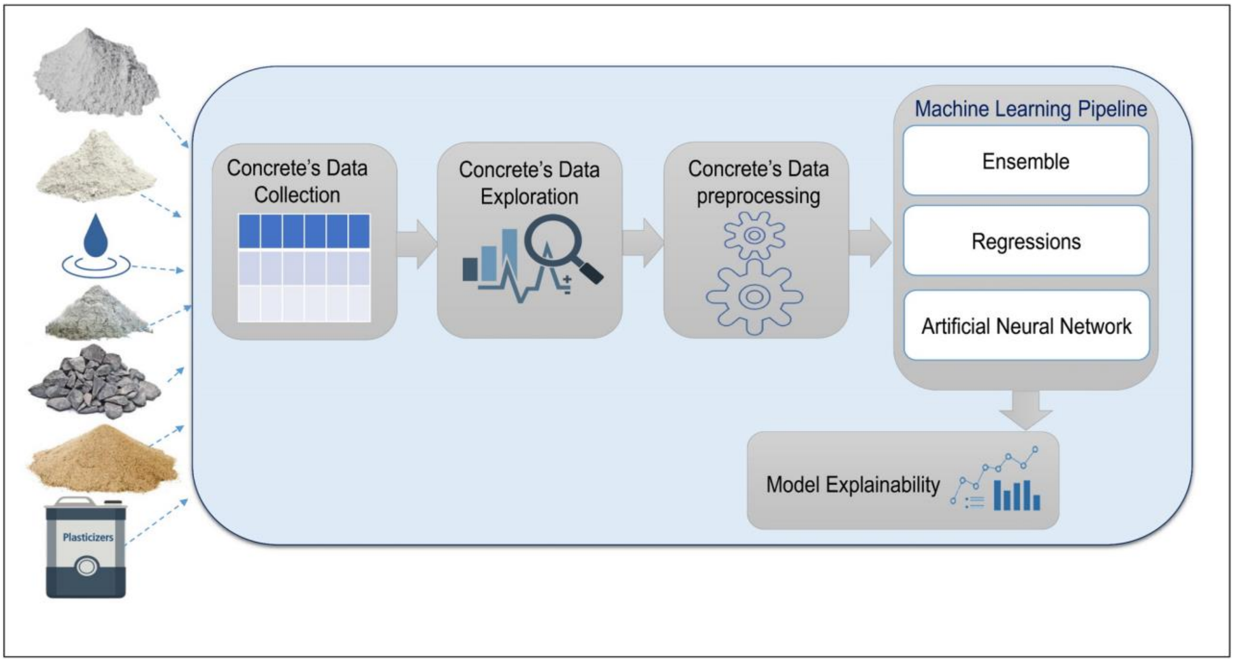
Problem Statement

The quality of concrete is determined by its compressive strength, which is measured using a conventional crushing test on a concrete cylinder.

The strength of the concrete is also a vital aspect in achieving the requisite longevity. It will take 28 days to test strength, which is a long period.

So, what will we do now?

We can save a lot of time and effort by using Data Science to estimate how much quantity of which raw material we need for acceptable compressive strength


Plasticizers
Concrete's Data Collection
Concrete's Data Exploration
Concrete's Data preprocessing
Machine Learning Pipeline
Ensemble
Regressions
Artificial Neural Network
Model Explainability

Objective :

To build a solution that should able to predict the compressive strength of the concrete. (Using Machine Learning)

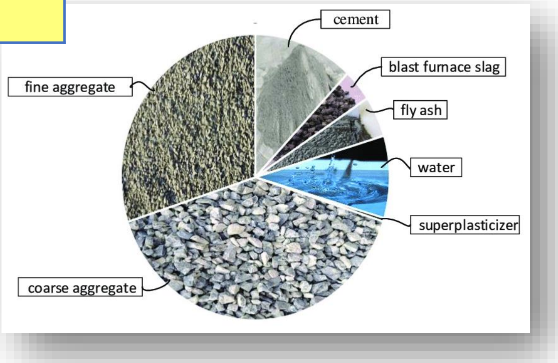
Approach:

The classical machine learning tasks like Data Exploration, Data Cleaning, Feature Engineering, Model Building and Model Testing.

Different machine learning algorithms that's best fit for the above case will be tried out..

Given Dataset

S.No	Variables	Units	Description
1	Cement	kg in a m^3 mixture	Feature/Input
2	Blast FurnaceSlag	kg in a m^3 mixture	Feature/Input
3	Fly Ash	kg in a m^3 mixture	Feature/Input
4	Water	kg in a m^3 mixture	Feature/Input
5	Superplasticizer	kg in a m^3 mixture	Feature/Input
6	Coarse Aggregate	kg in a m^3 mixture	Feature/Input
7	Fine Aggregate	kg in a m^3 mixture	Feature/Input
8	Age	kg in a m^3 mixture	Feature/Input
9	Concrete compressive strength	kg in a m^3 mixture	Target/Output



Number of instances (observations): 1030

Number of Attributes: 9

Attribute breakdown: 8 quantitative input variables, and 1 quantitative output variable

Link:

https://archive.ics.uci.edu/ml/datasets/Concrete+Compressive+Strength

Here's a brief explanation of each variable:

1.Cement: The amount of cement used in the concrete mix. Cement is the binding agent that holds concrete together.

2.Blast Furnace Slag: Blast furnace slag is a byproduct of iron production and is often used as a supplementary cementitious material in concrete to improve its properties.

3.Fly Ash: Fly ash is another supplementary cementitious material, typically derived from coal combustion, that is used in concrete to enhance its performance.

4.Water: The amount of water used in the concrete mix. Water is necessary for the hydration process of cement but must be carefully controlled to achieve desired concrete properties.

5.Superplasticizer: A type of chemical additive used in concrete to improve its workability and reduce the water-to-cement ratio without sacrificing strength.

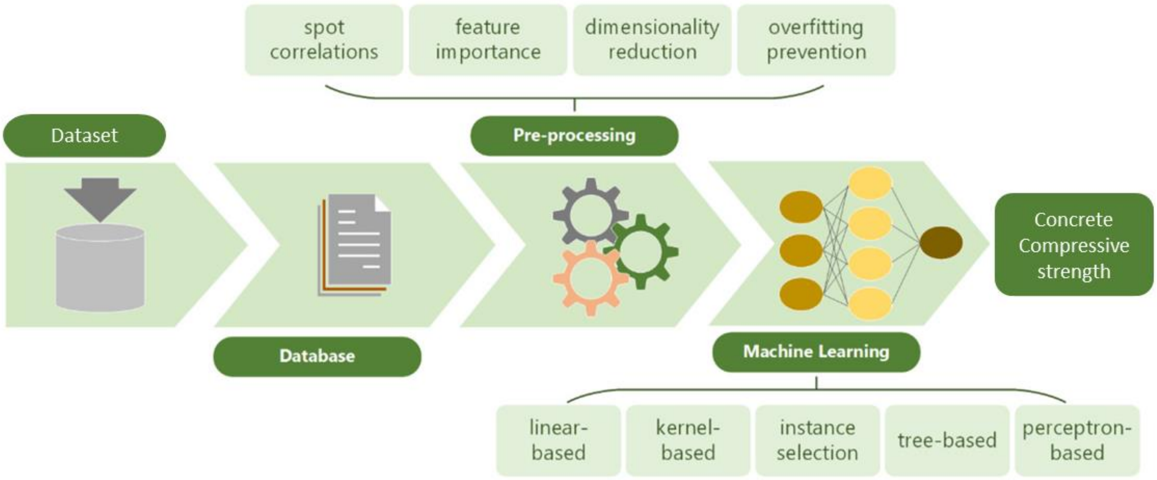
6.Coarse Aggregate: The portion of the aggregate in the concrete mix that consists of larger particles, such as gravel or crushed stone.

7.Fine Aggregate: The portion of the aggregate in the concrete mix that consists of smaller particles, such as sand.

8.Age: The age of the concrete specimen when its compressive strength was measured. Concrete strength typically increases with age due to ongoing hydration reactions.

9.Concrete Compressive Strength: The ultimate strength of the concrete, measured in units of pressure (e.g., megapascals or pounds per square inch), which indicates its ability to withstand compressive loads.

Steps



The following process steps were followed for the project

Data Collection: Gather relevant data containing features and the corresponding continuous target variable you want to predict.

Data Preprocessing: Clean the data, handle missing values, and preprocess features as necessary. For numerical features, you may need to scale or normalize them to ensure that they're on a similar scale.

Feature Engineering: Extract or create relevant features from the raw data that may help improve the model's predictive performance. This could involve transformations, interactions, or creating new features based on domain knowledge.

Model Selection: Choose a regression algorithm or model architecture suitable for your problem. Common regression algorithms include linear regression, decision trees, random forests, support vector regression, and neural networks.

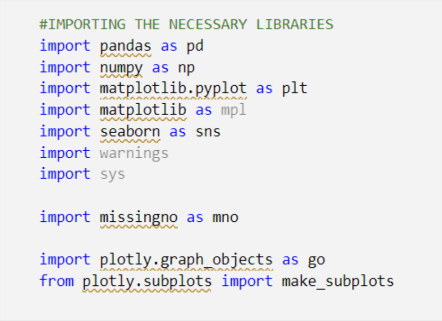
Model Training: Train the selected regression model on the training data. During training, the model learns the relationships between the features and the target variable by adjusting its parameters to minimize the error between its predictions and the actual target values.

Model Evaluation: Evaluate the trained regression model's performance using appropriate evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), or R-squared (coefficient of determination).

Hyperparameter Tuning: Fine-tune the model's hyperparameters to optimize its performance further. Hyperparameters for regression models may include regularization parameters, tree depth, learning rate, and batch size, among others.

Model Deployment: Once satisfied with the model's performance, deploy it into a production environment where it can make predictions on new data. Ensure that the deployment process is robust and scalable.

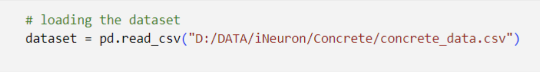
Import Packages and Create Dataframe



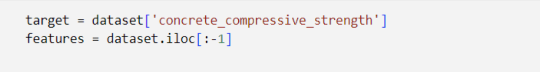
```
#IMPORTING THE NECESSARY LIBRARIES
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
import warnings
import sys

import missingno as mno

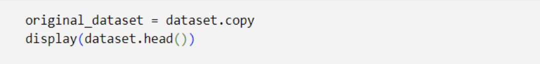
import plotly.graph_objects as go
from plotly.subplots import make_subplots
```



```
# loading the dataset
dataset = pd.read_csv("D:/DATA/iNeuron/Concrete/concrete_data.csv")
```



```
target = dataset['concrete_compressive_strength']
features = dataset.iloc[:-1]
```

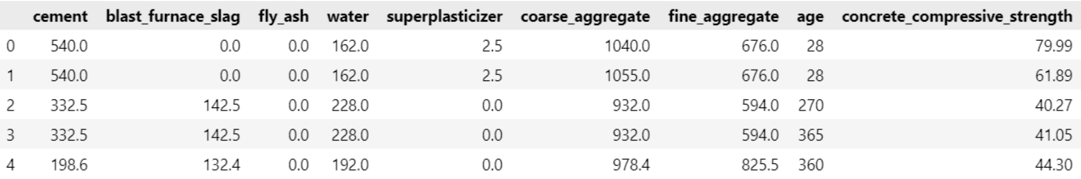


```
original_dataset = dataset.copy
display(dataset.head())
```

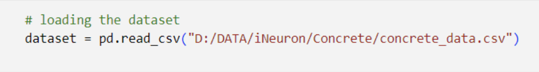
The above mentioned primary libraries and packages were imported and used for the project

python
NumPy
pandas
matplotlib
seaborn
scikit learn
XGBoost
SQLite
Joblib
Flask
web development,
one drop at a time
CSS
HTML

Dataset loaded and Created Dataframe



	cement	blast_furnace_slag	fly_ash	water	superplasticizer	coarse_aggregate	fine_aggregate	age	concrete_compressive_strength
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28	79.99
1	540.0	0.0	0.0	162.0	2.5	1055.0	676.0	28	61.89
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	270	40.27
3	332.5	142.5	0.0	228.0	0.0	932.0	594.0	365	41.05
4	198.6	132.4	0.0	192.0	0.0	978.4	825.5	360	44.30



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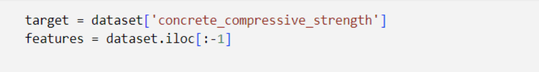
```



```
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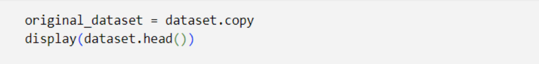
features = dataset.iloc[:-1]
```



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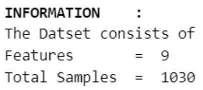
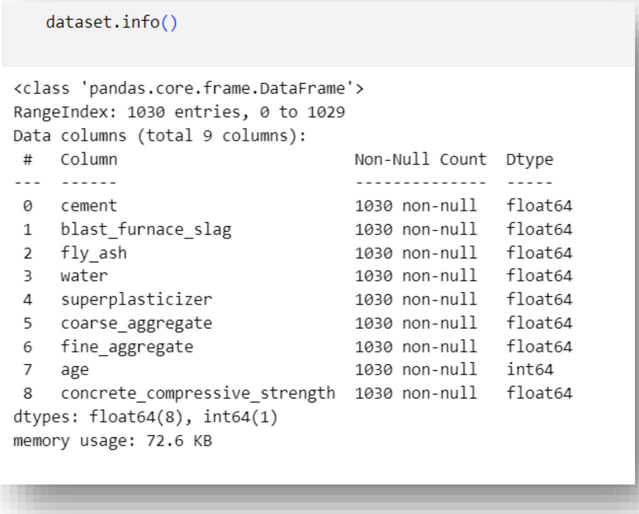


```
INFORMATION    :
The Datset consists of
Features       =  9
Total Samples  =  1030
```

The given Concrete dataset is loaded into the python environment

Checking the Dataframe



```
dataset.info()
```

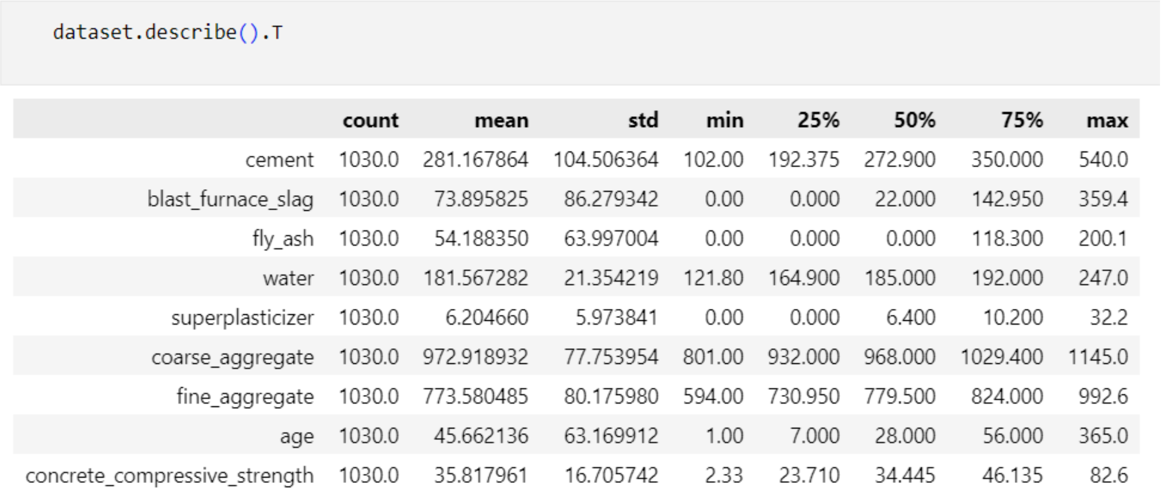
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1030 entries, 0 to 1029
Data columns (total 9 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   cement                         1030 non-null   float64
 1   blast_furnace_slag             1030 non-null   float64
 2   fly_ash                        1030 non-null   float64
 3   water                          1030 non-null   float64
 4   superplasticizer               1030 non-null   float64
 5   coarse_aggregate               1030 non-null   float64
 6   fine_aggregate                 1030 non-null   float64
 7   age                            1030 non-null   int64  
 8   concrete_compressive_strength  1030 non-null   float64
dtypes: float64(8), int64(1)
memory usage: 72.6 KB
```

The records of the Dataframe was checked

1) In the given dataset, All the columns are numerical

2) All the columns datatype belong to float64,
Except for the column 'age'

3) The data has 8 quantitative input variables and
only one quantitative output variable - concrete_compressive_strength



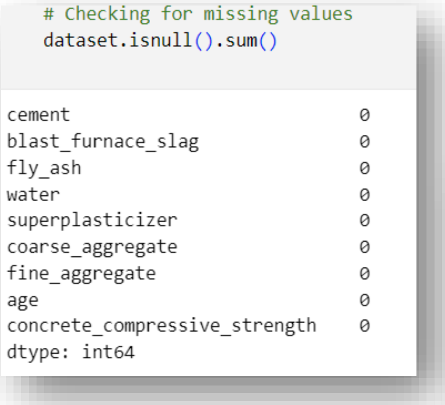
```
dataset.describe().T
```

	count	mean	std	min	25%	50%	75%	max
cement	1030.0	281.167864	104.506364	102.00	192.375	272.900	350.000	540.0
blast_furnace_slag	1030.0	73.895825	86.279342	0.00	0.000	22.000	142.950	359.4
fly_ash	1030.0	54.188350	63.997004	0.00	0.000	0.000	118.300	200.1
water	1030.0	181.567282	21.354219	121.80	164.900	185.000	192.000	247.0
superplasticizer	1030.0	6.204660	5.973841	0.00	0.000	6.400	10.200	32.2
coarse_aggregate	1030.0	972.918932	77.753954	801.00	932.000	968.000	1029.400	1145.0
fine_aggregate	1030.0	773.580485	80.175980	594.00	730.950	779.500	824.000	992.6
age	1030.0	45.662136	63.169912	1.00	7.000	28.000	56.000	365.0
concrete_compressive_strength	1030.0	35.817961	16.705742	2.33	23.710	34.445	46.135	82.6

The descriptive statistics of the dataset used for the project was checked

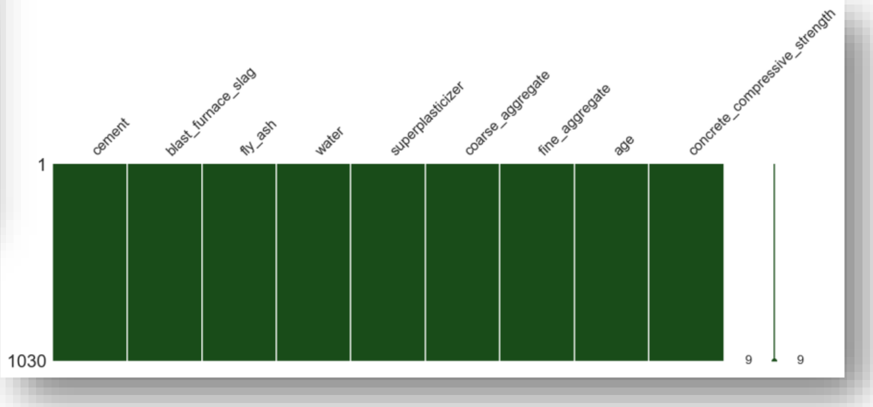
Data Cleaning:
•Check for and handle missing values in the dataset. Depending on the extent of missing data, you might choose to impute missing values or remove rows or columns with missing values.
•Check for and handle outliers that could skew the model's predictions. Outliers may need to be removed or transformed to better fit the distribution of the data.

Checking the Dataframe

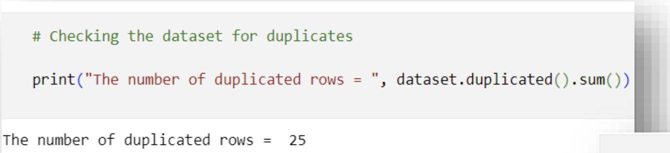


```
# Checking for missing values
dataset.isnull().sum()
```

```
cement                           0
blast_furnace_slag               0
fly_ash                          0
water                            0
superplasticizer                 0
coarse_aggregate                 0
fine_aggregate                   0
age                              0
concrete_compressive_strength    0
dtype: int64
```



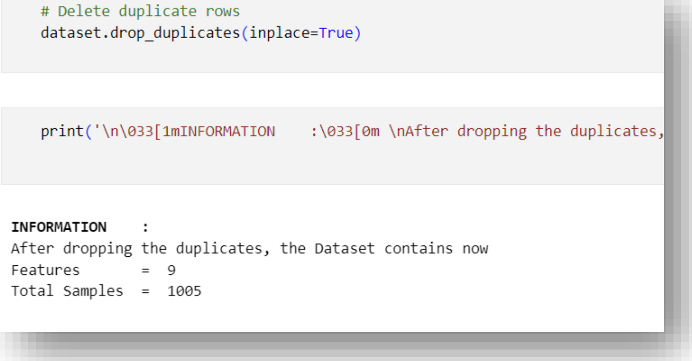
The records of the Dataframe was checked – 9 columns were found with non null values



```
# Checking the dataset for duplicates

print("The number of duplicated rows = ", dataset.duplicated().sum())
```

```
The number of duplicated rows =  25
```



```
# Delete duplicate rows
dataset.drop_duplicates(inplace=True)
```

```
print('\n\033[1mINFORMATION    :\033[0m \nAfter dropping the duplicates,
```

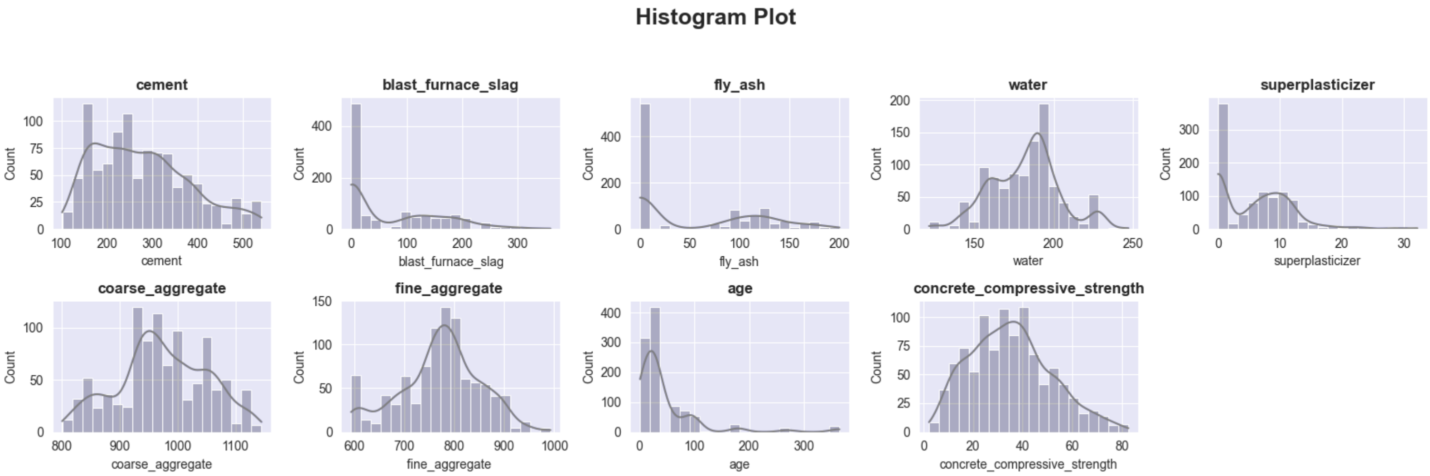
```
INFORMATION    :
After dropping the duplicates, the Dataset contains now
Features       =  9
Total Samples  =  1005
```

1) In the given dataset, 25 duplicate rows were found

2) All the duplicate rows were dropped from the dataset

3) Initially the dataset had 1030 rows and now after dropping the dataset has now has 1005 rows.

Visualizing the Dataframe



The distribution plots of all featured variables plotted to understand the distribution

Univariate analysis:

Cement - Right skewed distribution -- cement is skewed to higher values

Burnt Furnace Slag - Right skewed distribution -- slag is skewed to higher values and there are two gaussians

fly Ash - Right skewed distribution -- ash is skewed to higher values and there are two gaussians

Water - Moderately left skewed distribution

Superplasticizer - Right skewed distribution -- superplastic is skewed to higher values and there are two gaussians

Coarse aggregate - Moderately left skewed distribution

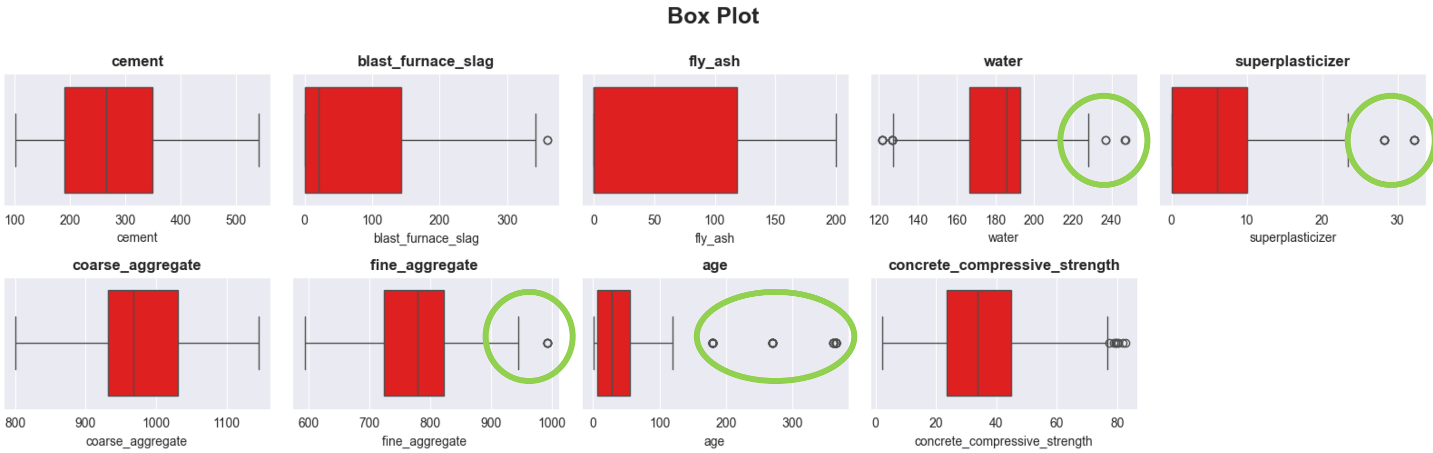
Fine aggregate - Moderately left skewed distribution

Age - Right skewed distribution -- age is skewed to higher values and there are five gaussians

Strength seems to be uniformly distributed

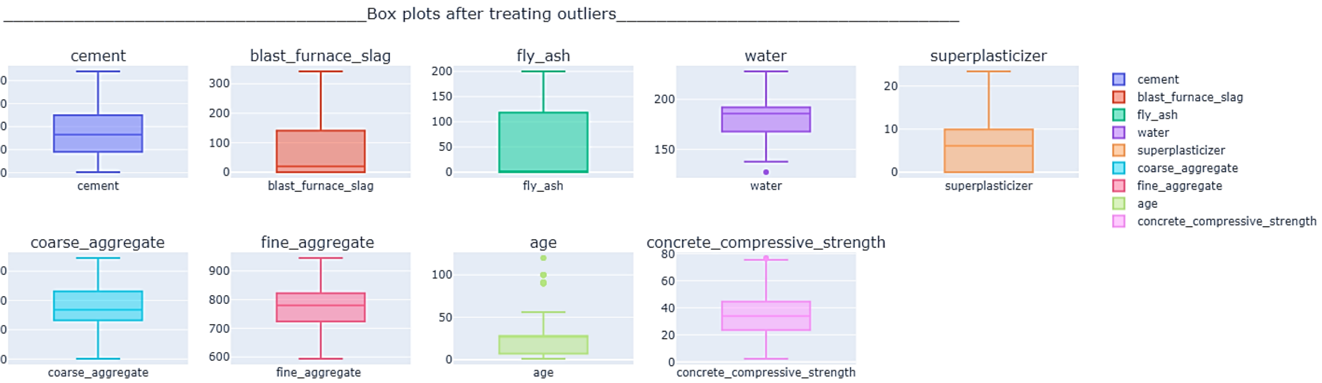
Visualizing the Dataframe

Detecting the Outliers



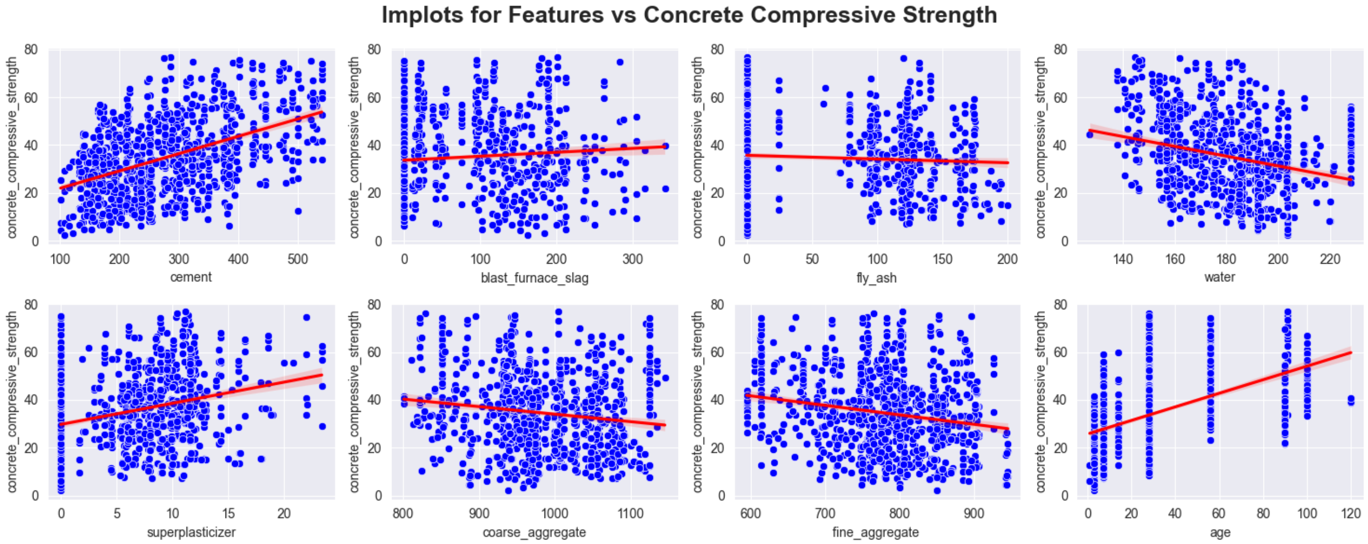
Several outliers have been detected , Next step is to remove outliers

Treating the Outliers



Removing outliers and plotting the data to check if removed

Visualizing the Dataframe


lmplots for Features vs Concrete Compressive Strength

Visualizing the data to understand each variable using bivariate analysis

Bivariate analysis:

1) Cement : Widely spread data can be observed , with a linear increase for most of the other features.

2) Burnt-furnace-slag : Seems to have a large amount of right skewed and clustered below 200 kg m^3 for most of the other features.

3) Fly Ash: Seems to have a dual distribution with values either zero or more than 100 kg m^3 for most of the other features.

4) Water : Widely spread data can be observed. with a negative linear relation with most of the features.

5) Superplastic :Largely clustered around 5 to 15 units , with a linear increase for most of the other features.

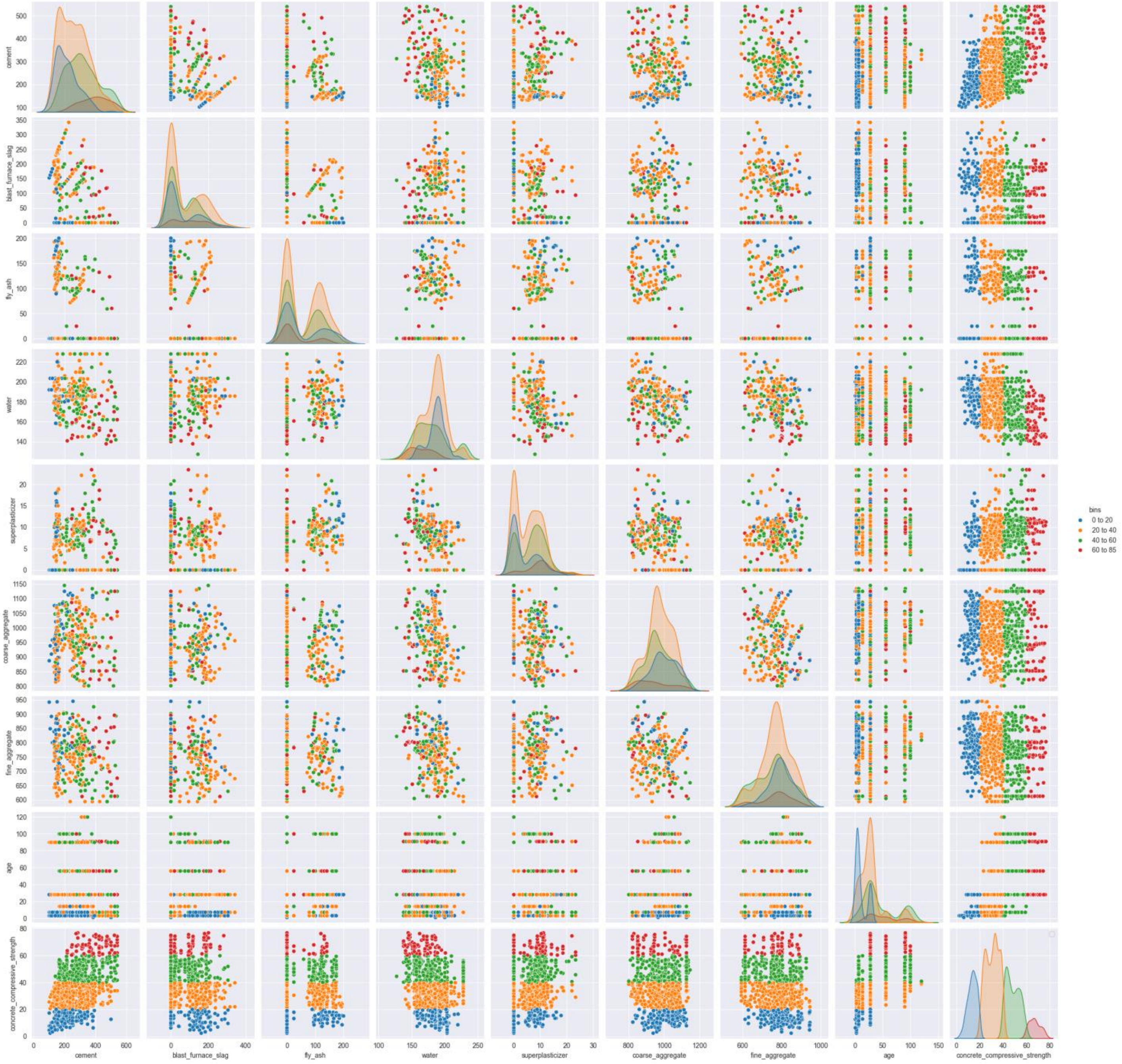
6) Coarse aggregate :Widely spread data can be observed. with a negative linear relation with most of the features.

7) Fine aggregate : Widely spread data can be observed. with a negative linear relation with most of the features.

8) Age : A linear increase for most of the other features. Large data seen for a low age count can be seen in the given dataset.

Visualizing the Dataframe

Pair Plot



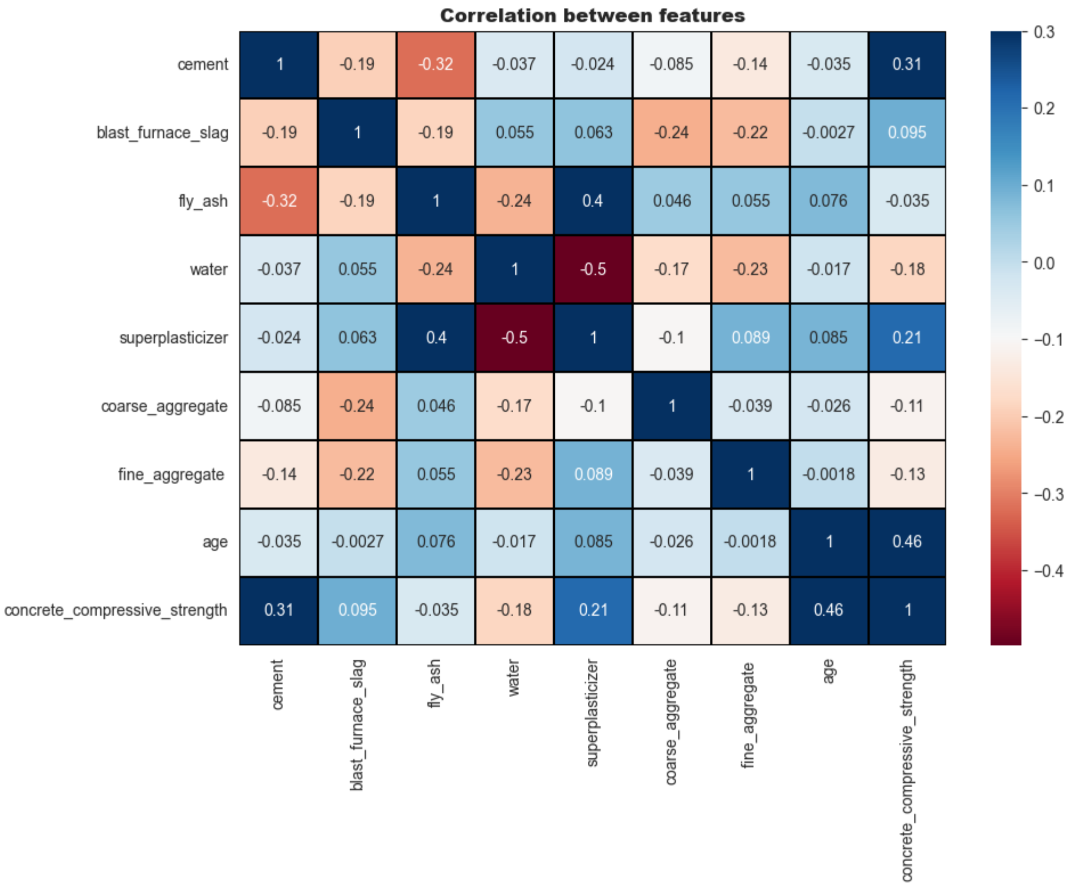
INFERENCE

From the pair plots, a Right skewed distribution is observed for majority of the features. Except for the aggregates and water.

At least 2 Gaussian (2 peaks) in furnace_Slag, fly_Ash, Superplasticer and Age, even though it's not unsupervised learning but in this dataset there are at least 2 clusters and there may be more.

Majority of the dataset is seen in the Range between 20 to 40 mPa for the concrete strength.

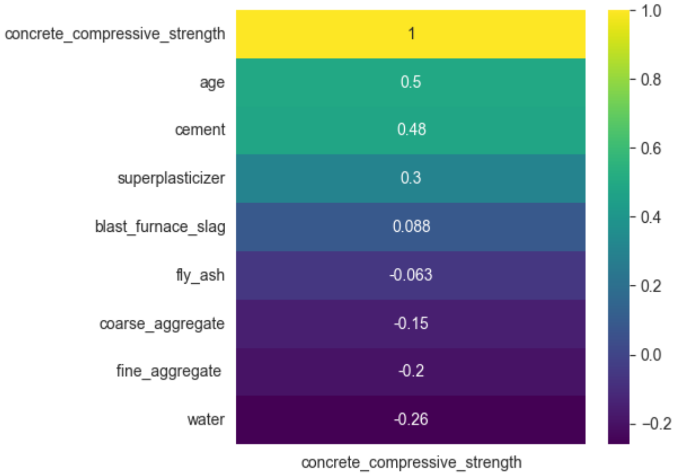
Visualizing the Dataframe



Concrete Compressive Strength

```
Age ,Cement, Superplasticizer and slag can be
observed to have good linear relationship compared
to other features

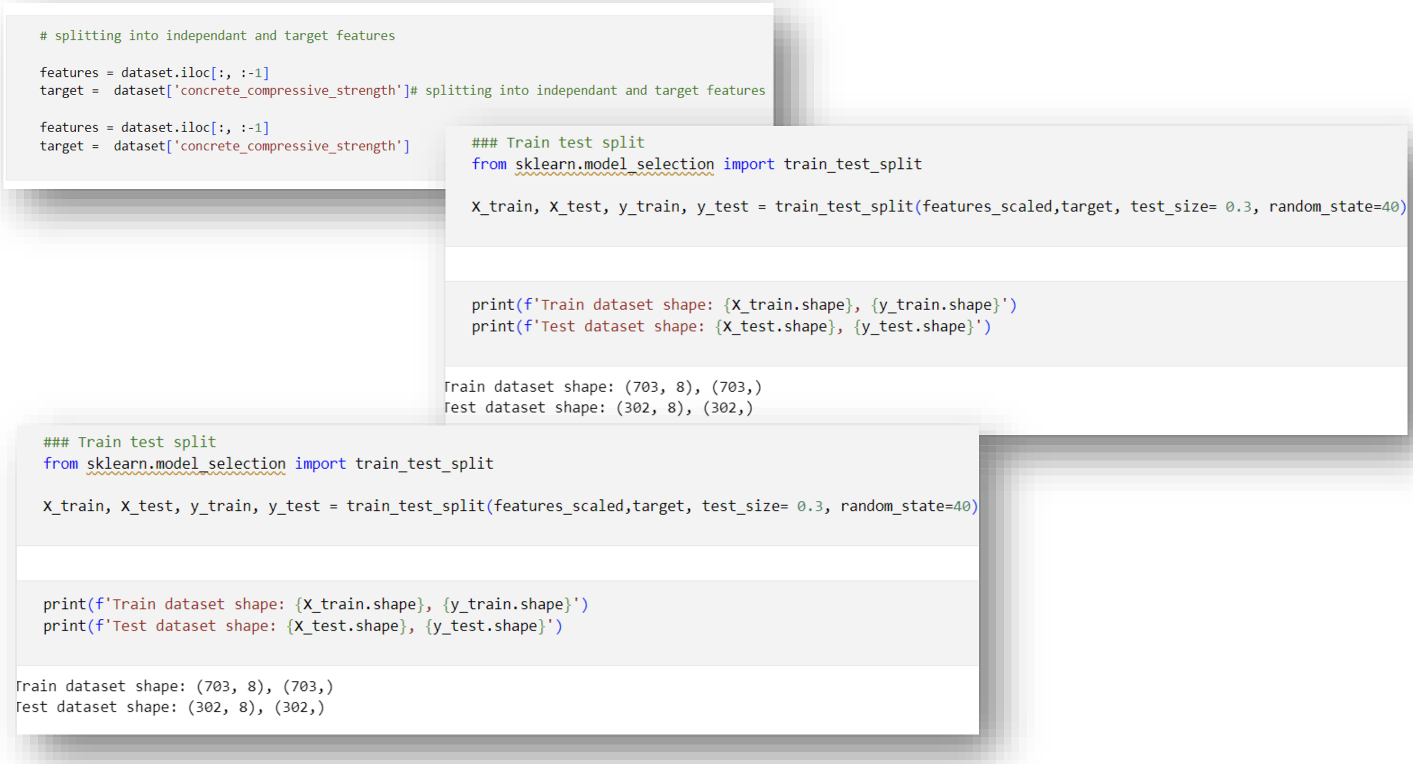
Water has a total negative correlation
```



Inference –
Only few variables seem to correlate with Concrete strength

1) Cement
2) Age
3) Superplasticizer
4) Blast furnace slag

Model Building



```
# splitting into independant and target features

features = dataset.iloc[:, :-1]
target =  dataset['concrete_compressive_strength']# splitting into independant and target features

features = dataset.iloc[:, :-1]
target =  dataset['concrete_compressive_strength']
```

```
### Train test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(features_scaled,target, test_size= 0.3, random_state=40)
```

```
print(f'Train dataset shape: {X_train.shape}, {y_train.shape}')
print(f'Test dataset shape: {X_test.shape}, {y_test.shape}')
```

```
Train dataset shape: (703, 8), (703,)
Test dataset shape: (302, 8), (302,)
```

```
### Train test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(features_scaled,target, test_size= 0.3, random_state=40)
```

```
print(f'Train dataset shape: {X_train.shape}, {y_train.shape}')
print(f'Test dataset shape: {X_test.shape}, {y_test.shape}')
```

```
Train dataset shape: (703, 8), (703,)
Test dataset shape: (302, 8), (302,)
```

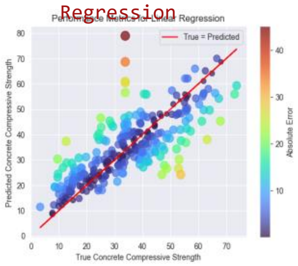
Data Modeling:

Since this is a Regression problem, I tried to build using few common Regression models for our training data and then compare performance of each model on test data to accurately predict target variable

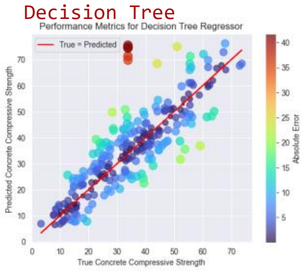
Linear Regression
Decision Tree
Gradient Boosting Regr
Random Forest Regr

KNN Regressor
SVM Regressor
Ridge Regression
Lasso Regression

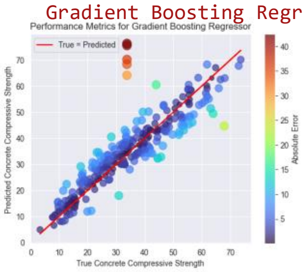
Linear Regression



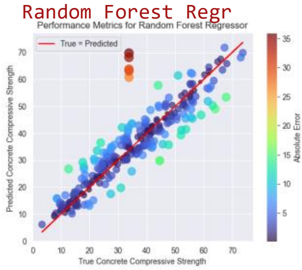
Decision Tree

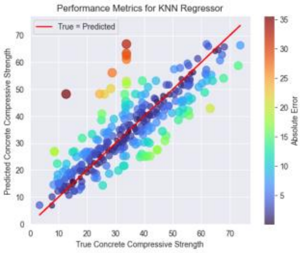


Gradient Boosting Regr

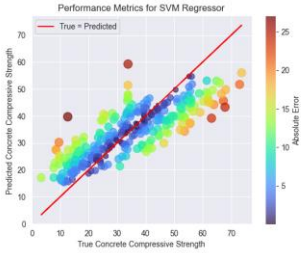


Random Forest Regr

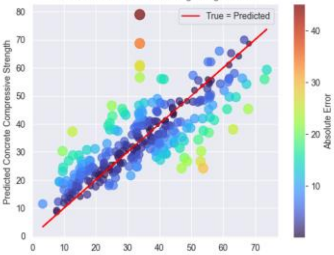




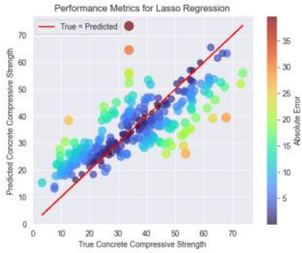
KNN Regressor



SVM Regressor



Ridge Regression



Lasso Regression

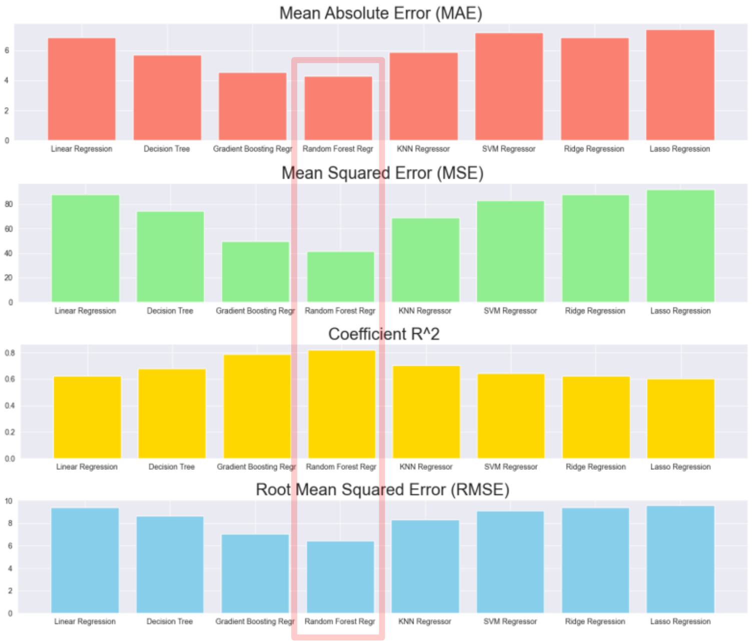
Models testing Output

Comparing all the models – to find out the best model

S No.	Model No.	RMSE	MAE	MSE	R2
1	Linear Regression	9.390438	6.860813	88.180334	0.622271
2	Decision Tree	8.627499	5.691987	74.433745	0.681156
3	Gradient Boosting Regr	7.039062	4.541052	49.548396	0.787755
4	Random Forest Regr	6.443462	4.290236	41.518202	0.822153
5	KNN Regressor	8.303886	5.885437	68.954524	0.704627
6	SVM Regressor	9.124020	7.199210	83.247745	0.643400
7	Ridge Regression	9.387114	6.862371	88.117918	0.622538
8	Lasso Regression	9.606232	7.417111	92.279699	0.604711

Inference

Looking at the data we can clearly see that the Random Forest algorithm does a better job in all the metrics as compared to all the other classifiers.



Inference

Looking at the data we can clearly see that the Random Forest algorithm does a better job in all the metrics as compared to all the other classifiers.

Models testing Output

Inference

Random Forest algorithm was chosen to do the final prediction as it gave the best parameters.

```
n_estimators = [100, 200, 500]
max_depths = [30, 50, 70]
min_samples_leafs = [2, 5, 10]
```

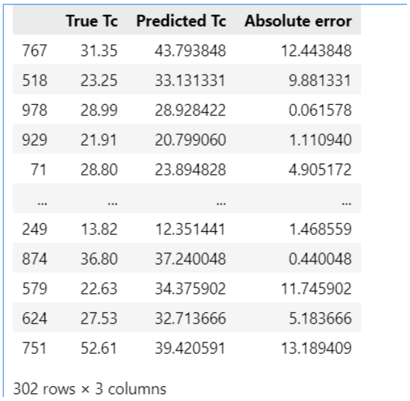
With the above mentioned parameters Model hypertuning was carried out for random forest algorithm

An improved R2 of 83.13 % was obtained

Model No.	RMSE	MAE	MSE	R2
Random Forest Regr	6.443462	4.290236	41.518202	0.822153

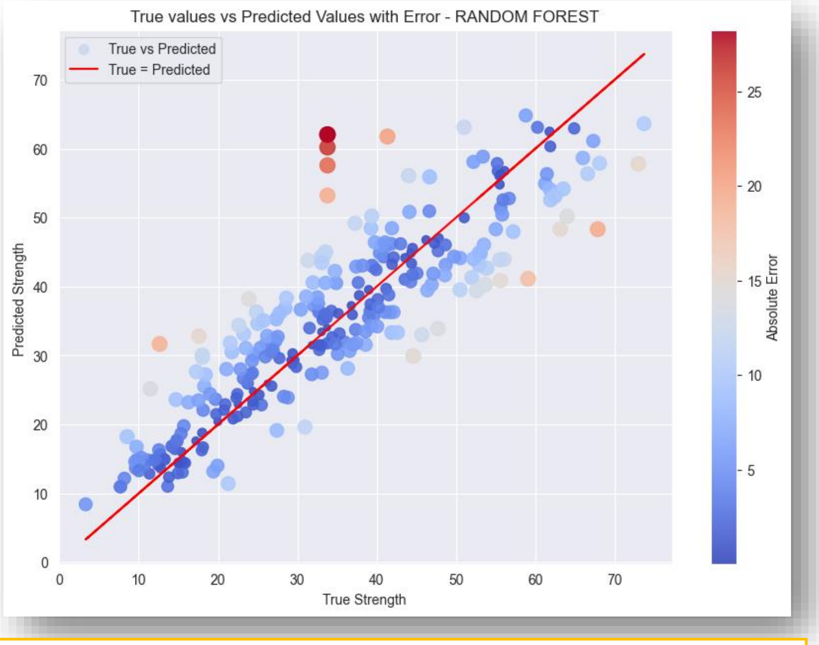
Estimator	Max Depth	Min Samples Leaf	R2 Score	MSE	MAE	RMSE
200	30	2	0.831345	39.37236	4.219989	6.27474

Final Model Output



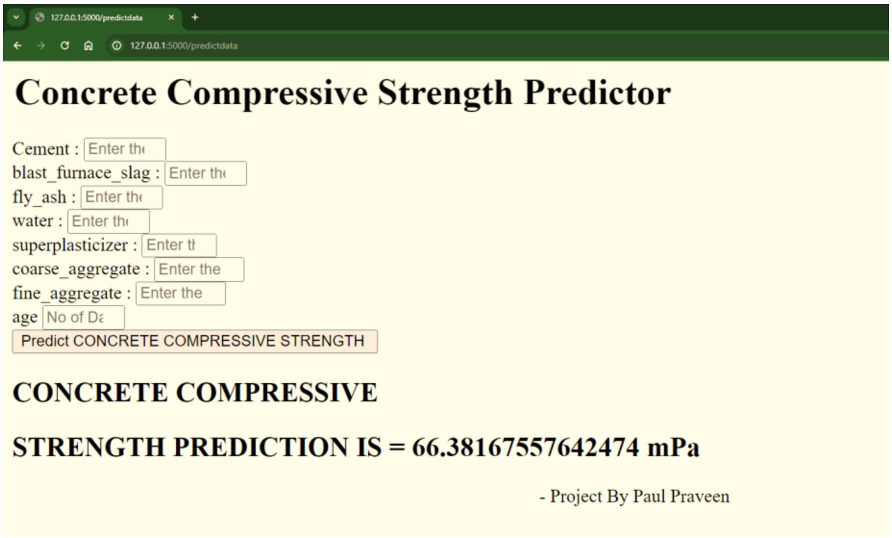
	True Tc	Predicted Tc	Absolute error
767	31.35	43.793848	12.443848
518	23.25	33.131331	9.881331
978	28.99	28.928422	0.061578
929	21.91	20.799060	1.110940
71	28.80	23.894828	4.905172
...	...	...	...
249	13.82	12.351441	1.468559
874	36.80	37.240048	0.440048
579	22.63	34.375902	11.745902
624	27.53	32.713666	5.183666
751	52.61	39.420591	13.189409

302 rows × 3 columns



Applying Random forest algorithm to build final model

Final Model Deployment



Concrete Compressive Strength Predictor

Cement : Enter the
blast_furnace_slag : Enter the
fly_ash : Enter the
water : Enter the
superplasticizer : Enter th
coarse_aggregate : Enter the
fine_aggregate : Enter the
age No of Da

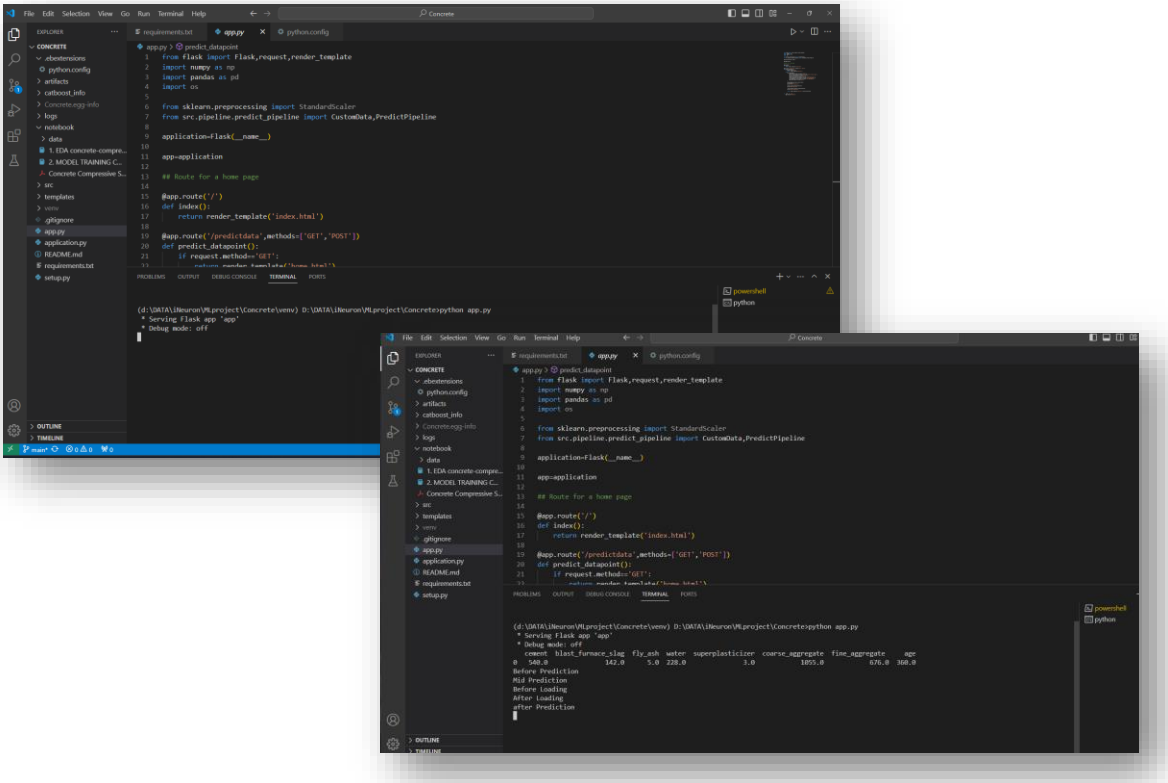
Predict CONCRETE COMPRESSIVE STRENGTH

CONCRETE COMPRESSIVE

STRENGTH PREDICTION IS = 66.38167557642474 mPa

- Project By Paul Praveen

Using Flask to deploy the model



```python
from flask import Flask,request,render_template
import numpy as np
import pandas as pd
import os

from sklearn.preprocessing import StandardScaler
from src.pipeline.predict_pipeline import CustomData,PredictPipeline

application=Flask(__name__)

app=application

## Route for a home page

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/predictdata',methods=['GET','POST'])
def predict_datapoint():
    if request.method=='GET':
        return render_template('home.html')
```

```
(d:\DATA\iNeuron\MLproject\Concrete\venv) D:\DATA\iNeuron\MLproject\Concrete>python app.py
 * Serving Flask app 'app'
 * Debug mode: off
```

```python
from flask import Flask,request,render_template
import numpy as np
import pandas as pd
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from sklearn.preprocessing import StandardScaler
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```
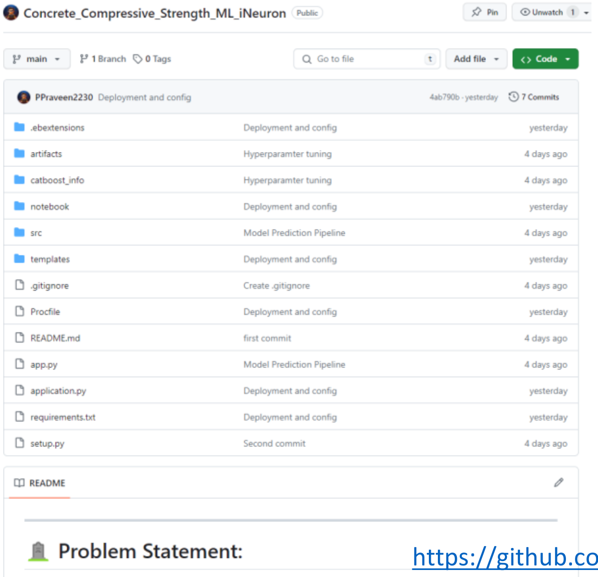

```
(d:\DATA\iNeuron\MLproject\Concrete\venv) D:\DATA\iNeuron\MLproject\Concrete>python app.py
 * Serving Flask app 'app'
 * Debug mode: off
   cement  blast_furnace_slag  fly_ash  water  superplasticizer  coarse_aggregate  fine_aggregate    age
0   540.0               142.0      5.0  228.0               3.0            1055.0           676.0  360.0
Before Prediction
Mid Prediction
Before Loading
After Loading
after Prediction
```

Git hub Repository



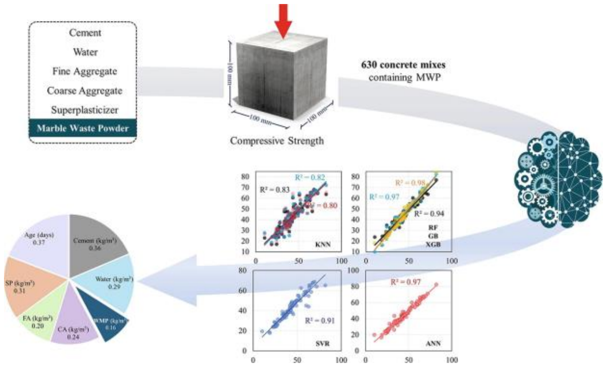
Concrete_Compressive_Strength_ML_iNeuron Public

PPraveen2230 Deployment and config 4ab790b · yesterday 7 Commits

.ebextensions	Deployment and config	yesterday
artifacts	Hyperparamter tuning	4 days ago
catboost_info	Hyperparamter tuning	4 days ago
notebook	Deployment and config	yesterday
src	Model Prediction Pipeline	4 days ago
templates	Deployment and config	yesterday
.gitignore	Create .gitignore	4 days ago
Procfile	Deployment and config	yesterday
README.md	first commit	4 days ago
app.py	Model Prediction Pipeline	4 days ago
application.py	Deployment and config	yesterday
requirements.txt	Deployment and config	yesterday
setup.py	Second commit	4 days ago

README

Problem Statement:



https://github.com/PPraveen2230/Concrete_Compressive_Strength_ML_iNeuron.git

The Project being uploaded in my Git hub repository

Conclusion

1. Concrete compressive strength using original features with an accuracy of 84 % on test data were predicted from this project

2. Results from various methods of analysis shows us that we got the best accuracy from original features and followed below steps to gain that much of accuracy.

a. As mentioned in Multi-variate analysis, there are some non-linear(curvy-linear) relationship within independent features as well as with target variable hence polynomial features were implemented.

b. Simple linear regression with polynomial features with degree = 2 performs better on both training and test set with 1% difference.

3. We had 25 duplicate instances in dataset and dropped those duplicates.

4. We had outliers in 'Water', 'Superplastic', 'Fineagg', 'Age' and 'Strength' column also, handled these outliers by replacing every outlier with upper and lower side of the whisker.

5. Except 'Cement', 'Superplastic' , 'slag' and 'Age' features, all other features are having very weak relationship with concrete 'Strength' feature and does not account for making statistical decision (of correlation).

6. Range of clusters in this dataset is 2 to 6

7. No missing values were found in dataset.

8. **Finally Random Forest Regressor model with an accuracy of 84 % is our best model.**

Model No.	RMSE	MAE	MSE	R2
Random Forest Regr	6.443462	4.290236	41.5182	0.822153
Gradient Boosting Regr	7.039062	4.541052	49.5484	0.787755
KNN Regressor	8.303886	5.885437	68.95452	0.704627

Estimator	Max Depth	Min Samples Leaf	R2 Score	MSE	MAE	RMSE
200	30	2	0.831345	39.37236	4.219989	6.27474