Predicting Compressive Strength of Concrete using IBM Watson AutoAI Experiment

Introduction :

- ### Overview -

The project is about predicting compressive strength of concrete using IBM Watson Auto AI Experiment. This comes under the category of "Machine Learning". The main objective of the project is to predict the strength of the concrete.

- ### Purpose -

Concrete is a material used in construction that has great versatility and which is used across the globe. Concrete has several advantages, including good compressive strength, durability,work ability, construction availability, and low cost. Determining accurate concrete strength is a major civil engineering problem. Test results of 28- day concrete cylinder represent the characteristic strength of the concrete that has been prepared and cast to form the concrete work. It is important to wait 28 days to ensure the quality control of the process, although it is very time consuming. Thereby, this model helps to predict the compressive strength of concrete from early age test results.

Literature Survey :

- ### Existing Problem -

Determining accurate concrete strength is a major civil engineering problem. It takes 28 days to know the characteristic strength of the concrete that has been prepared. So it is important to wait till 28 days to ensure the quality of the concrete. Therefore, it is very time consuming.

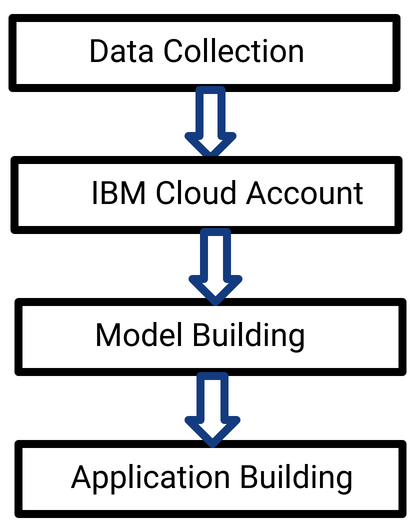
Proposed Solution -

An ability to predict the compressive strength of concrete early allows constructors to quickly understand the concrete's probable weaknesses and make a decision to manage a destruction process or continue with construction. Further, to the benefit of both user (and purchaser) and producer, reliably and rapidly predicting the results of a 28-day test would benefit all stakeholders as opposed to waiting the full, conventional, 28 days. We are building a Machine Learning model to predict the compressive strength of concrete using IBM Watson AutoAI Machine Learning Service. The model is deployed on IBM cloud to get scoring end point which can be used as API in mobile app or web app building. We are developing a web application which is built using node red service. We make use of the scoring end point to give user input values to the deployed model. The model prediction is then showcased on User Interface.

Theoretical Analysis :

Block Diagram -

Steps to be followed to build our application:



➢ Hardware/Software Desigining :

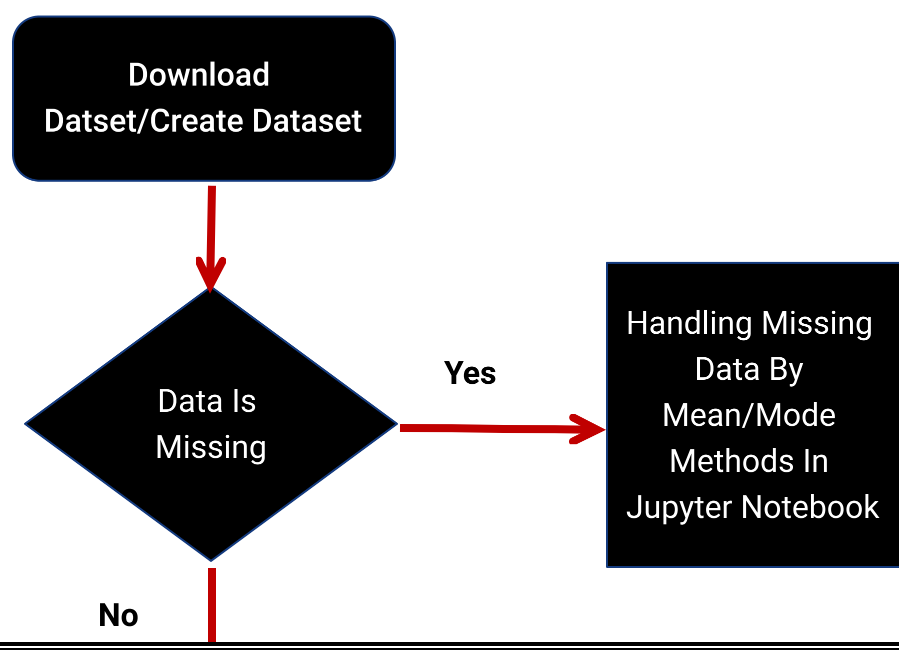
- Jupyter Notebook for data analysis.
- IBM Cloud
- Creating IBM Watson Studio AutoAI Experiment.
- Building user interface with Nodered.

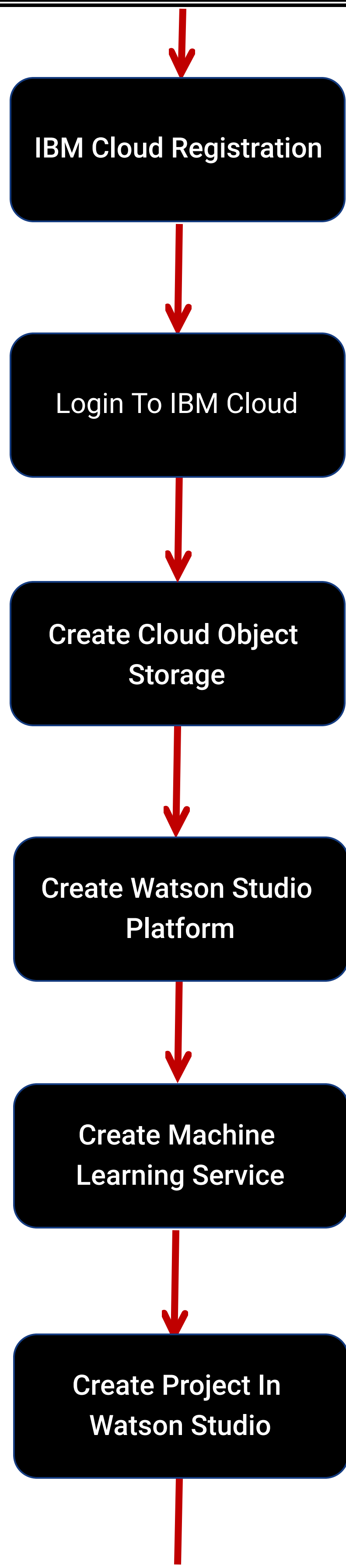
Experimental Investigations :

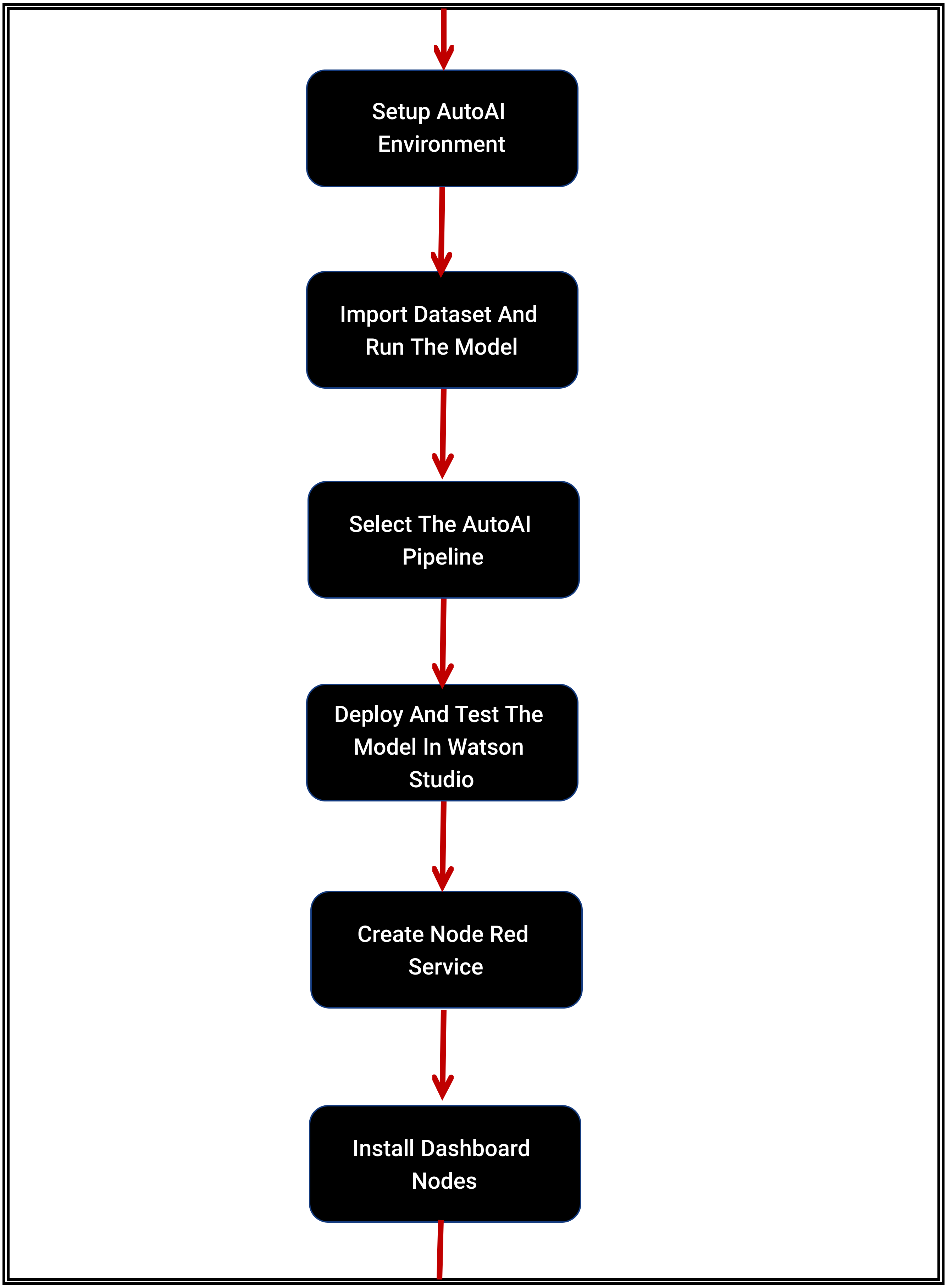
Upon analysis of the dataset we understand that :

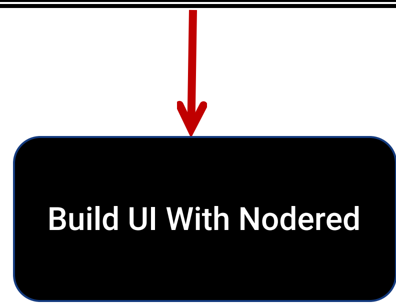
- ➢ As the dataset consists of multiple independent input attributes and an output attribute is to be predicted, it comes under superised learning.
- ➢ As the output is continuous and not categorical, regression algorithm should be used, but as we are using AutoAI here, any regression is not applied externally.
- ➢ Since there are multiple columns, we have to analyse which columns have importance using various methods and extract the important ones.
- ➢ So from the visualization we can say that cement, water, superplasticizer and age are the important parameters for determining the strength of the concrete.

Flowchart :




IBM Cloud Registration
Login To IBM Cloud
Create Cloud Object Storage
Create Watson Studio Platform
Create Machine Learning Service
Create Project In Watson Studio


Setup AutoAI Environment
Import Dataset And Run The Model
Select The AutoAI Pipeline
Deploy And Test The Model In Watson Studio
Create Node Red Service
Install Dashboard Nodes



Result :

The model is successfully trained and deployed using AutoAI experiment and Node Red Service. Therefore, **"The Compressive Strength Of The Concrete"**, Machine Learning model can predict the compressive strength of concrete.

Advantages and Disadvantages :

➢ Advantages -

- Fast model selection. Select top-performing models in only minutes.
- Predicting the compressive strength of concrete early allows constructors to quickly understand the concrete's probable weaknesses and make a decision to manage a destruction process or continue with construction.

➢ Disadvantages -

- Sometime slow due to network glitch.
- Data must be good going in.
- Model can't be edited yet in a more granular way.

Applications :

- Using AutoAI, we can build and deploy a machine learning model with sophisticated training features and no coding. The tool does most of the work for us.
- Benefits all stakeholders as they need not wait till 28 days to know the compressive strength of the concrete.

Conclusion :

Therefore, the **"Predicting Compressive Strength of Concrete using IBM Watson AutoAI Experiment", Machine Learning** model is created and the purpose of the project is fulfilled.

Future Scope :

This model, right now is effective mainly for predicting the compressive strength of concrete so that constructors can easily understand the concrete probable weakness. By upgrading the dataset, this application can also be used to make predictions in other sectors.

Bibliography :

- github.com
- smartinternz.com
- thesmartbridge.com
- cloud.ibm.com

Appendix :

(Source code)

- ✔ **To check for any null values in the dataset -**

```
from numpy import *
from pandas import *
from matplotlib.pyplot import *
import seaborn as sns
d=read_csv('Concrete Data.csv')
d
d.corr()
d.info()
sns.heatmap(d.corr(),annot=True)
d.isnull().any()
```

Screenshots

- **Data Collection :**

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Cement (c	Blast Furn	Fly Ash (c	Water (cc	Superplas	Coarse Ag	Fine Aggr	Age (day)	Concrete compressive strength(MPa, megapascals)				
2	540	0	0	162	2.5	1040	676	28	79.99				
3	540	0	0	162	2.5	1055	676	28	61.89				
4	332.5	142.5	0	228	0	932	594	270	40.27				
5	332.5	142.5	0	228	0	932	594	365	41.05				
6	198.6	132.4	0	192	0	978.4	825.5	360	44.3				
7	266	114	0	228	0	932	670	90	47.03				
8	380	95	0	228	0	932	594	365	43.7				
9	380	95	0	228	0	932	594	28	36.45				
10	266	114	0	228	0	932	670	28	45.85				
11	475	0	0	228	0	932	594	28	39.29				
12	198.6	132.4	0	192	0	978.4	825.5	90	38.07				
13	198.6	132.4	0	192	0	978.4	825.5	28	28.02				
14	427.5	47.5	0	228	0	932	594	270	43.01				
15	190	190	0	228	0	932	670	90	42.33				
16	304	76	0	228	0	932	670	28	47.81				
17	380	0	0	228	0	932	670	90	52.91				
18	139.6	209.4	0	192	0	1047	806.9	90	39.36				
19	342	38	0	228	0	932	670	365	56.14				
20	380	95	0	228	0	932	594	90	40.56				
21	475	0	0	228	0	932	594	180	42.62				
22	427.5	47.5	0	228	0	932	594	180	41.84				
23	139.6	209.4	0	192	0	1047	806.9	28	28.24				

- **Importing required libraries :**

```
In [1]: from numpy import *
        from pandas import *
        from matplotlib.pyplot import *
        import seaborn as sns
```

- **Importing dataset :**

```
In [2]: d=read_csv('Concrete Data.csv')
        d
```

Out[2]:

	Cement (component 1)(kg in a m^3 mixture)	Blast Furnace Slag (component 2)(kg in a m^3 mixture)	Fly Ash (component 3)(kg in a m^3 mixture)	Water (component 4)(kg in a m^3 mixture)	Superplasticizer (component 5)(kg in a m^3 mixture)	Coarse Aggregate (component 6)(kg in a m^3 mixture)	Fine Aggregate (component 7)(kg in a m^3 mixture)	Age (day)	Concrete compressive strength(MPa, megapascals)
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
...	...	...	...	...	...	...	...	...	...
1025	276.4	116.0	90.3	179.6	8.9	870.1	768.3	28	44.28
1026	322.2	0.0	115.6	196.0	10.4	817.9	813.4	28	31.18
1027	148.5	139.4	108.6	192.7	6.1	892.4	780.0	28	23.70
1028	159.1	186.7	0.0	175.6	11.3	989.6	788.9	28	32.77
1029	260.9	100.5	78.3	200.6	8.6	864.5	761.5	28	32.40

1030 rows × 9 columns

- **Finding correlation between the attributes :**

```
In [3]: d.corr()
```

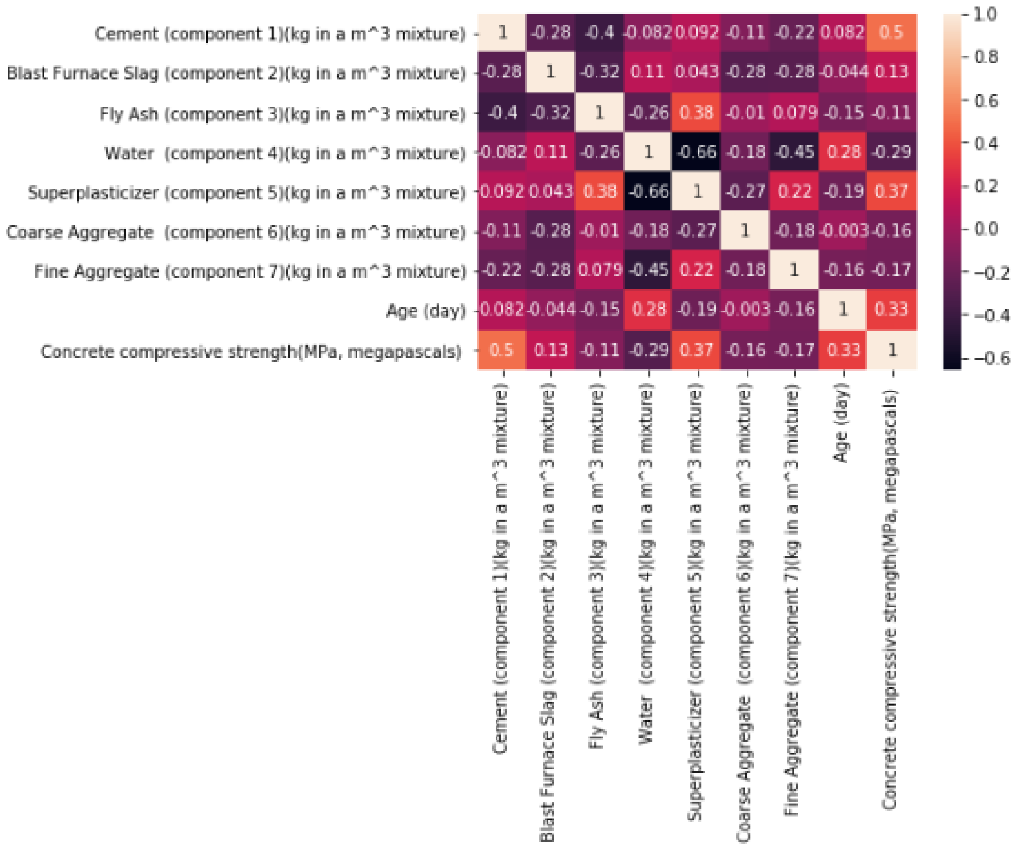
Out[3]:

	Cement (component 1)(kg in a m^3 mixture)	Blast Furnace Slag (component 2)(kg in a m^3 mixture)	Fly Ash (component 3)(kg in a m^3 mixture)	Water (component 4)(kg in a m^3 mixture)	Superplasticizer (component 5)(kg in a m^3 mixture)	Coarse Aggregate (component 6)(kg in a m^3 mixture)	Fine Aggregate (component 7)(kg in a m^3 mixture)	Age (day)	Concrete compressive strength(MPa, megapascals)
Cement (component 1)(kg in a m^3 mixture)	1.000000	-0.275216	-0.397467	-0.081587	0.092386	-0.109349	-0.222718	0.081946	0.497832
Blast Furnace Slag (component 2)(kg in a m^3 mixture)	-0.275216	1.000000	-0.323580	0.107252	0.043270	-0.283999	-0.281603	-0.044246	0.134829
Fly Ash (component 3)(kg in a m^3 mixture)	-0.397467	-0.323580	1.000000	-0.256984	0.377503	-0.009961	0.079108	-0.154371	-0.105755
Water (component 4)(kg in a m^3 mixture)	-0.081587	0.107252	-0.256984	1.000000	-0.657533	-0.182294	-0.450661	0.277618	-0.289633
Superplasticizer (component 5)(kg in a m^3 mixture)	0.092386	0.043270	0.377503	-0.657533	1.000000	-0.265999	0.222691	-0.192700	0.366079
Coarse Aggregate (component 6)(kg in a m^3 mixture)	-0.109349	-0.283999	-0.009961	-0.182294	-0.265999	1.000000	-0.178481	-0.003016	-0.164935
Fine Aggregate (component 7)(kg in a m^3 mixture)	-0.222718	-0.281603	0.079108	-0.450661	0.222691	-0.178481	1.000000	-0.156095	-0.167241
Age (day)	0.081946	-0.044246	-0.154371	0.277618	-0.192700	-0.003016	-0.156095	1.000000	0.328873
Concrete compressive strength(MPa, megapascals)	0.497832	0.134829	-0.105755	-0.289633	0.366079	-0.164935	-0.167241	0.328873	1.000000

- **Data Visualisation :**

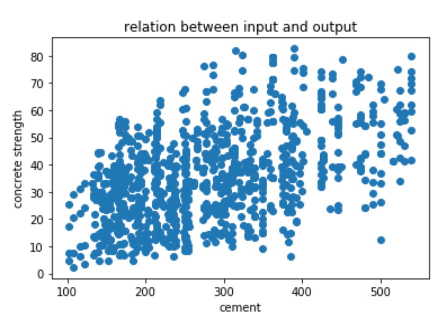
```
In [5]: sns.heatmap(d.corr(),annot=True)
```

```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1ed05ebf188>
```




```
In [18]: scatter(d.iloc[:,0],y)
         xlabel('cement')
         ylabel('concrete strength')
         title('relation between input and output')
```

```
Out[18]: Text(0.5, 1.0, 'relation between input and output')
```

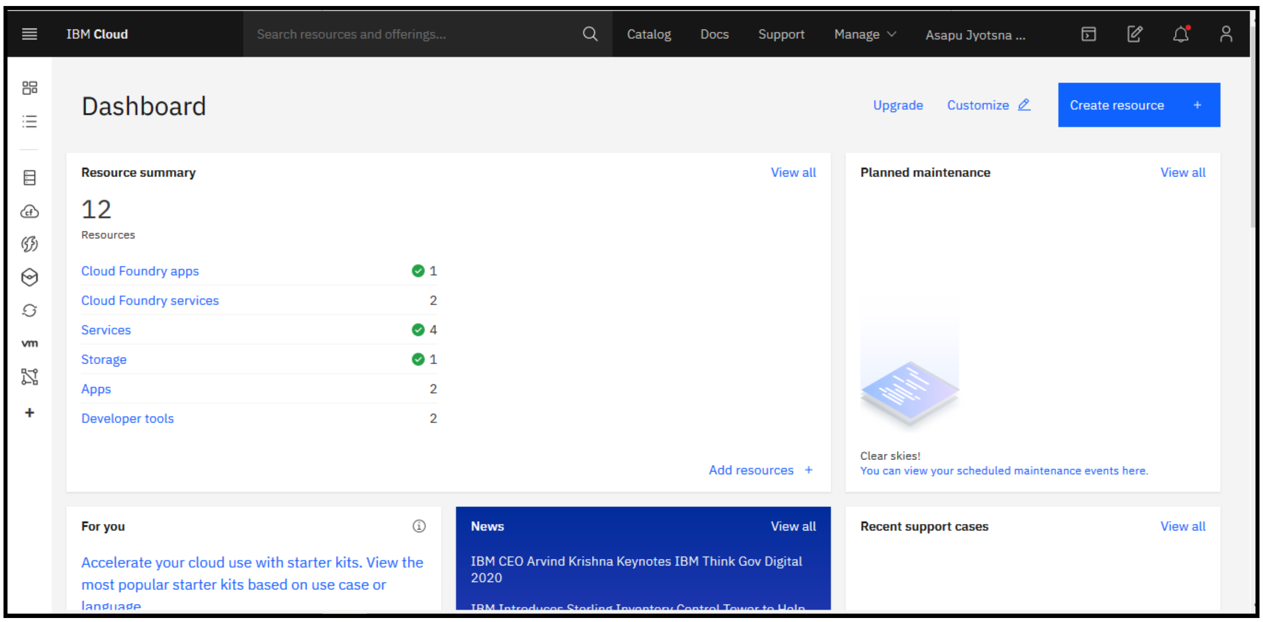


- **Checking for null values :**

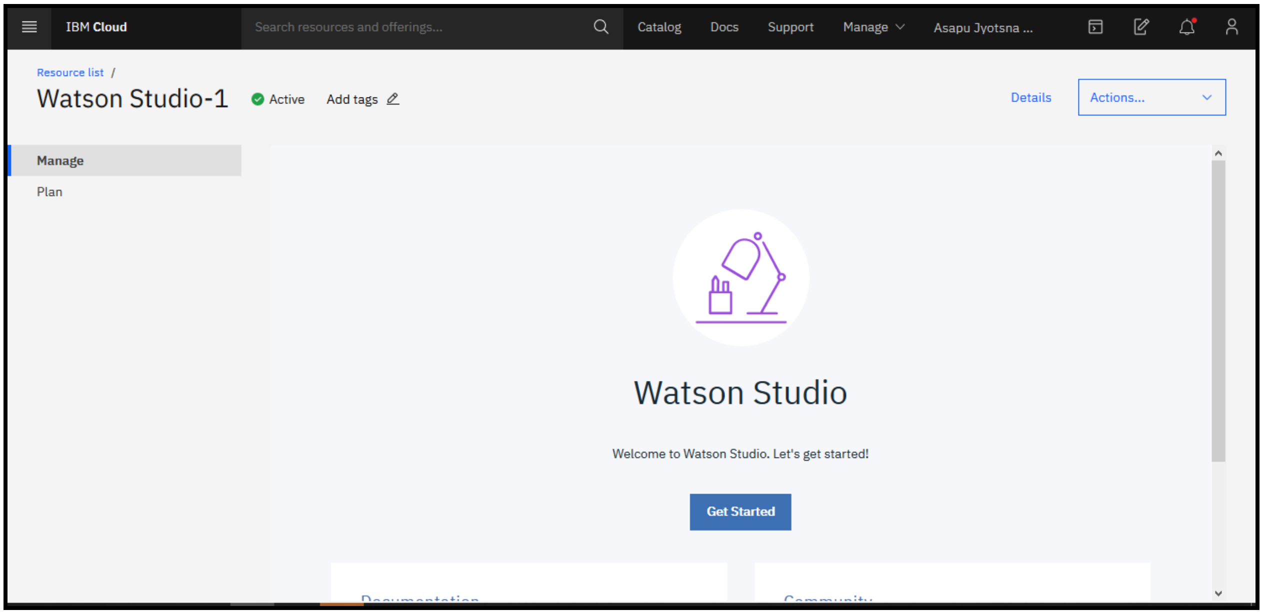
```
In [6]: d.isnull().any()

Out[6]: Cement (component 1)(kg in a m^3 mixture)                False
        Blast Furnace Slag (component 2)(kg in a m^3 mixture)    False
        Fly Ash (component 3)(kg in a m^3 mixture)               False
        Water  (component 4)(kg in a m^3 mixture)                False
        Superplasticizer (component 5)(kg in a m^3 mixture)      False
        Coarse Aggregate  (component 6)(kg in a m^3 mixture)     False
        Fine Aggregate (component 7)(kg in a m^3 mixture)        False
        Age (day)                                                False
        Concrete compressive strength(MPa, megapascals)          False
        dtype: bool
```

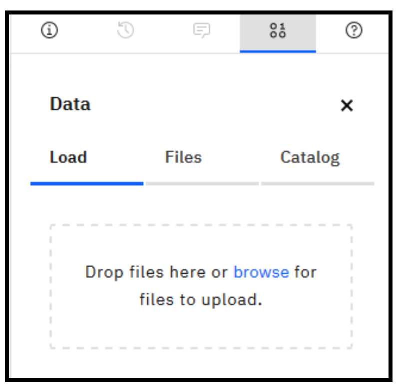
- **Creating IBM account :**

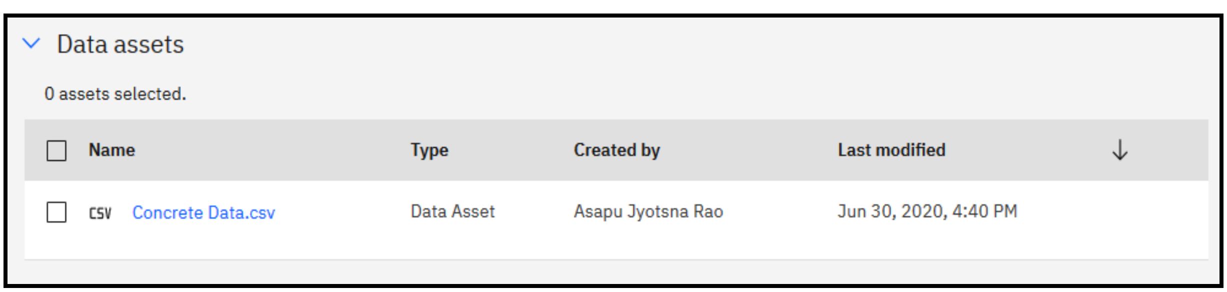


- **Watson Studio Platform :**



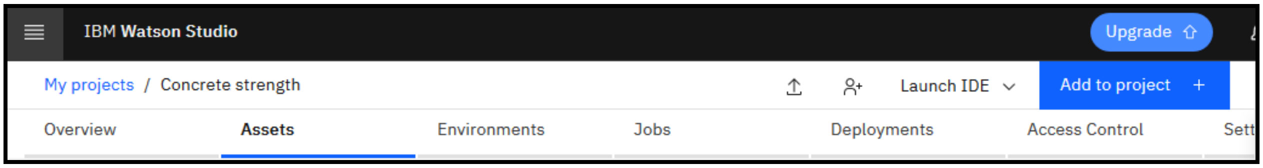
- **Uploading dataset :**



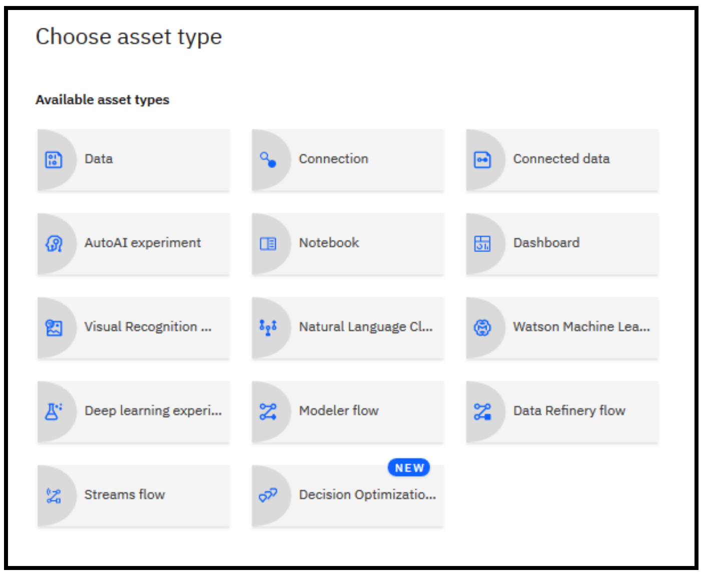


● Creating AutoAI Environment :

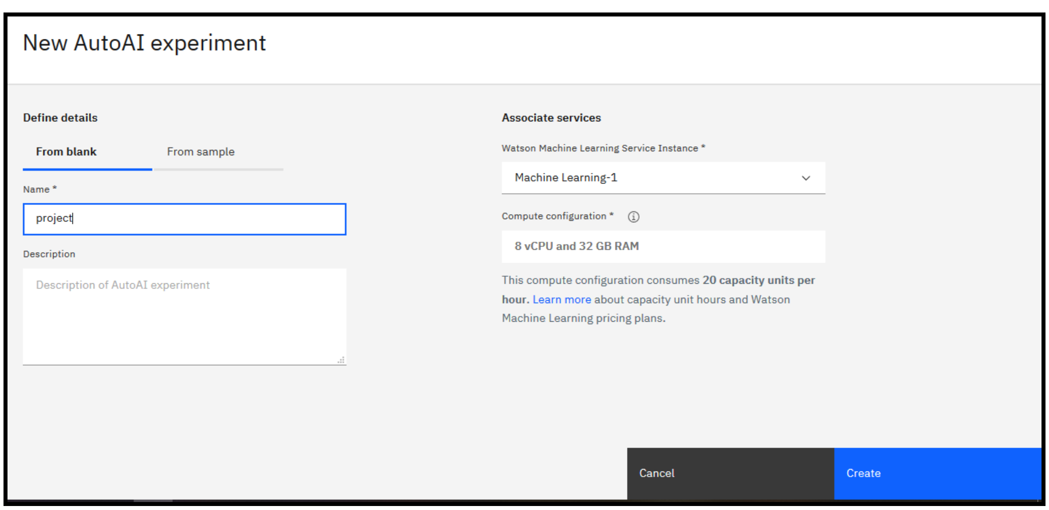
✔ Click on Add to project -



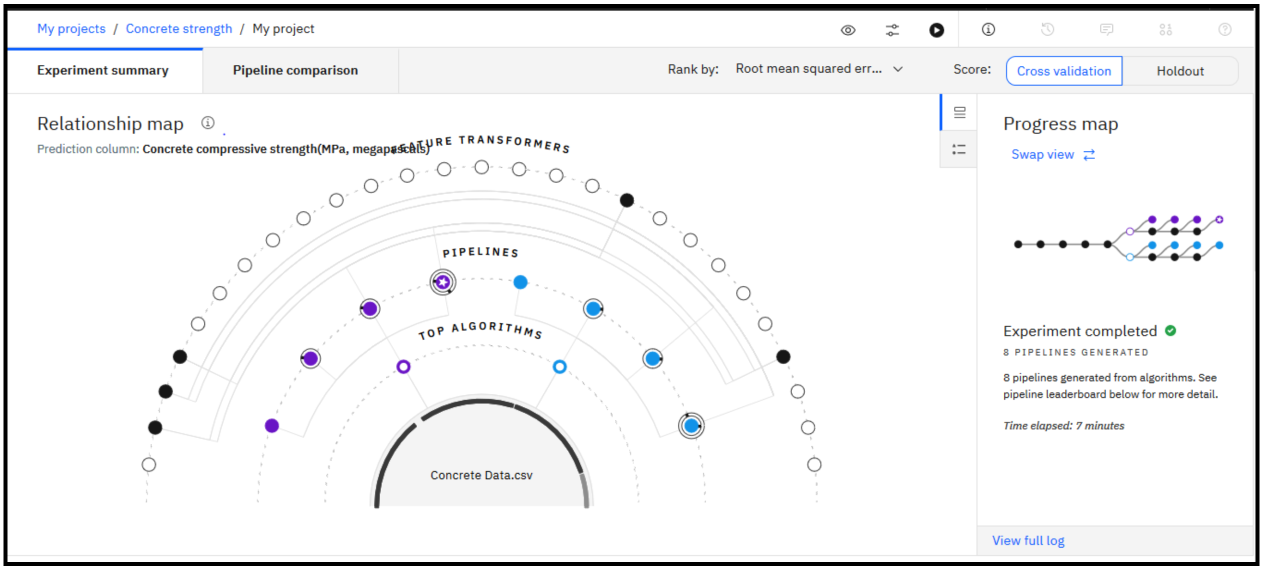
✔ Select AutoAI experiment as asset type -



✔ Create the Environment-



- **Running the model :**



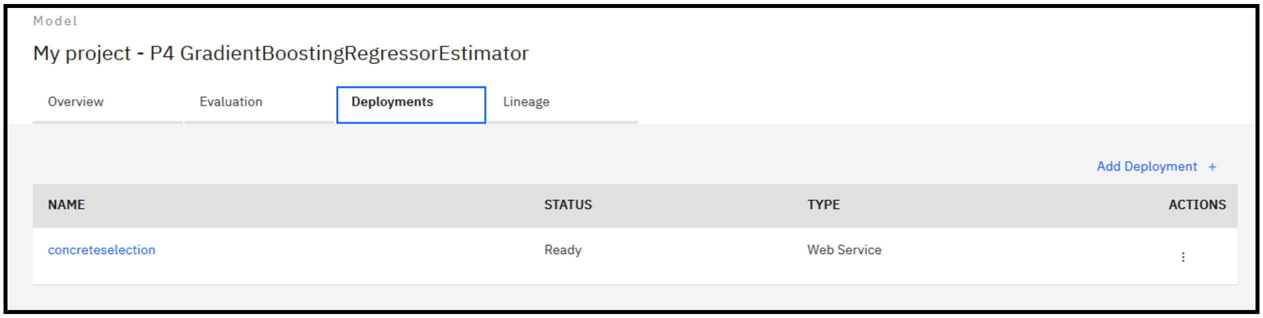
- **Pipeline Selection :**

Pipeline leaderboard

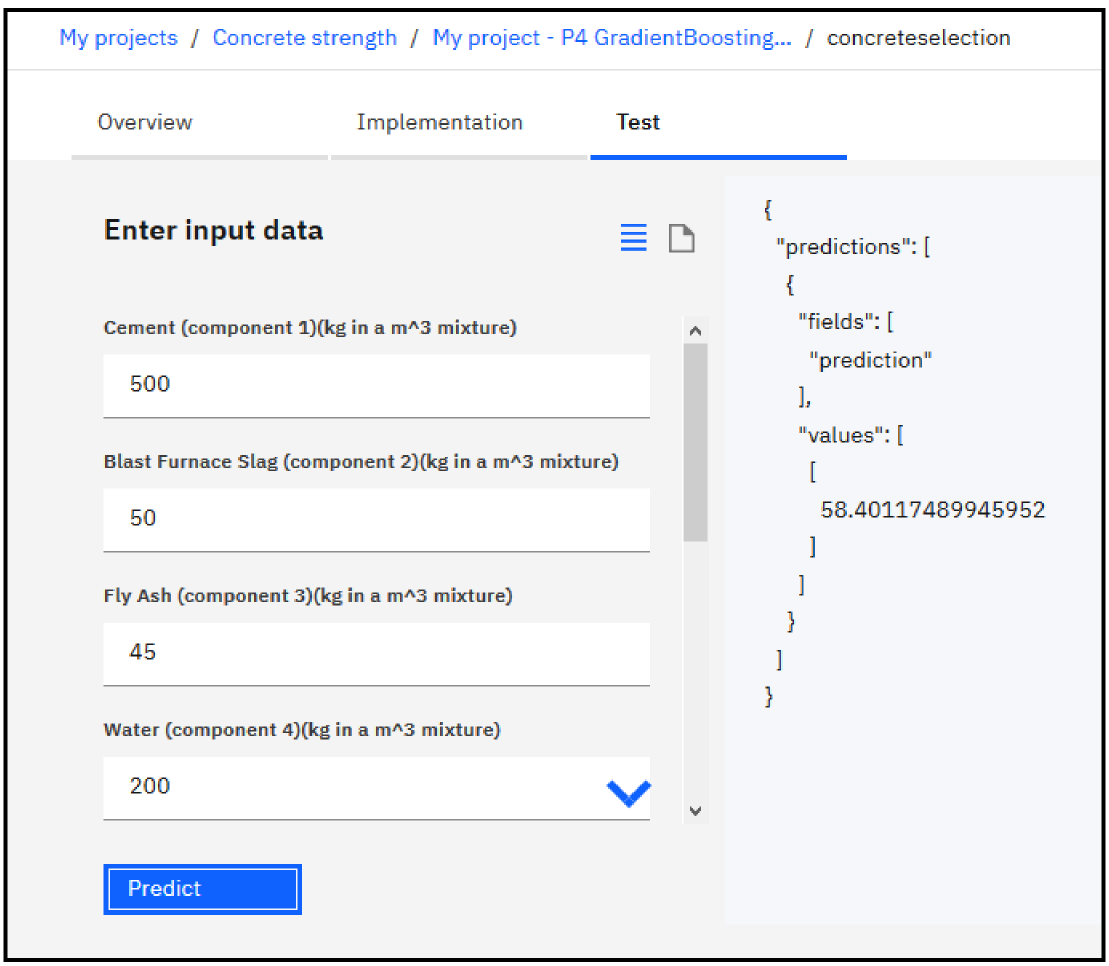
Rank	Name	Algorithm	RMSE (Optimized)	Enhancements	Build time
★ 1	Pipeline 4	Gradient Boosting Regressor	4.502	HPO-1 FE HPO-2	00:00:23
2	Pipeline 3	Gradient Boosting Regressor	4.598	HPO-1 FE	00:02:20
3	Pipeline 2	Gradient Boosting Regressor	4.878	HPO-1	00:00:13
4	Pipeline 1	Gradient Boosting Regressor	5.330	*None*	00:00:01
5	Pipeline 7	Random Forest Regressor	5.471	HPO-1 FE	00:00:45
6	Pipeline 8	Random Forest Regressor	5.471	HPO-1 FE HPO-2	00:00:40
7	Pipeline 5	Random Forest Regressor	5.843	*None*	00:00:01

- **Deploying the model :**

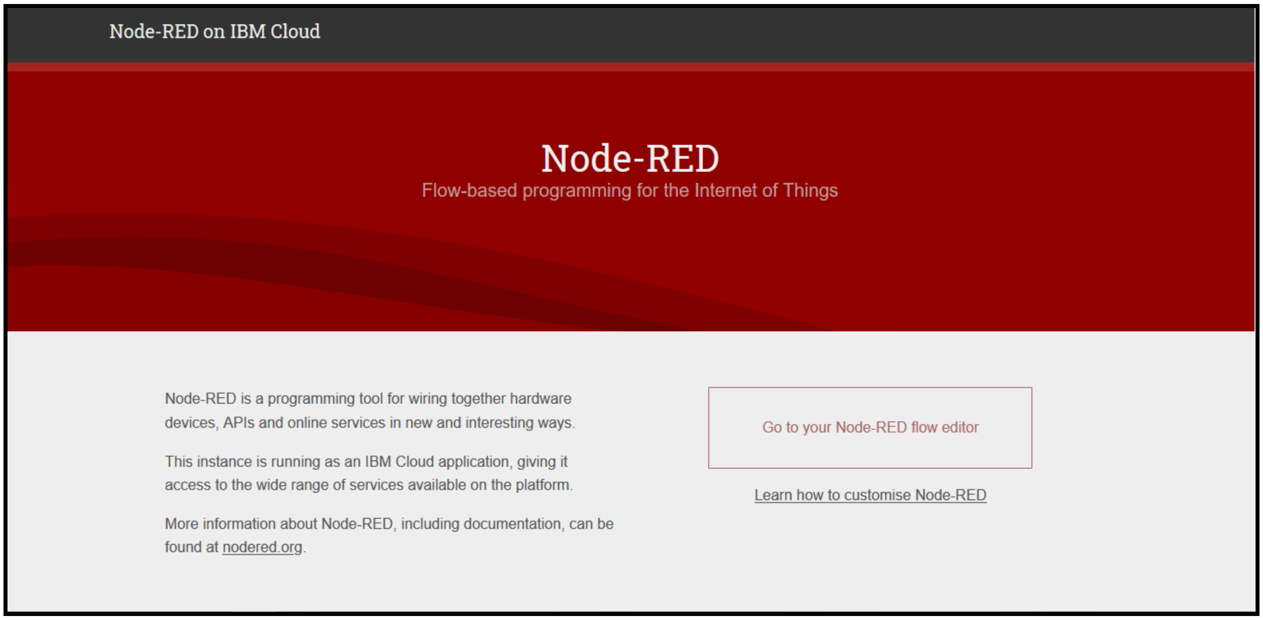
✔ click on add deployment and deploy the model -



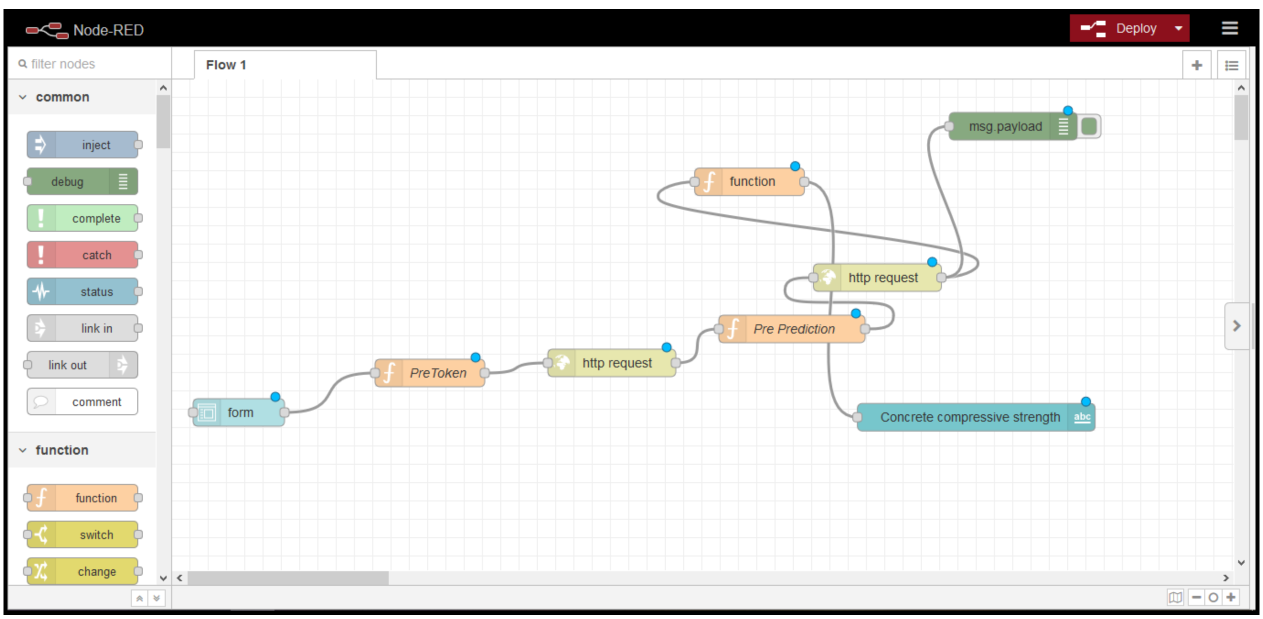
- **Testing the data :**



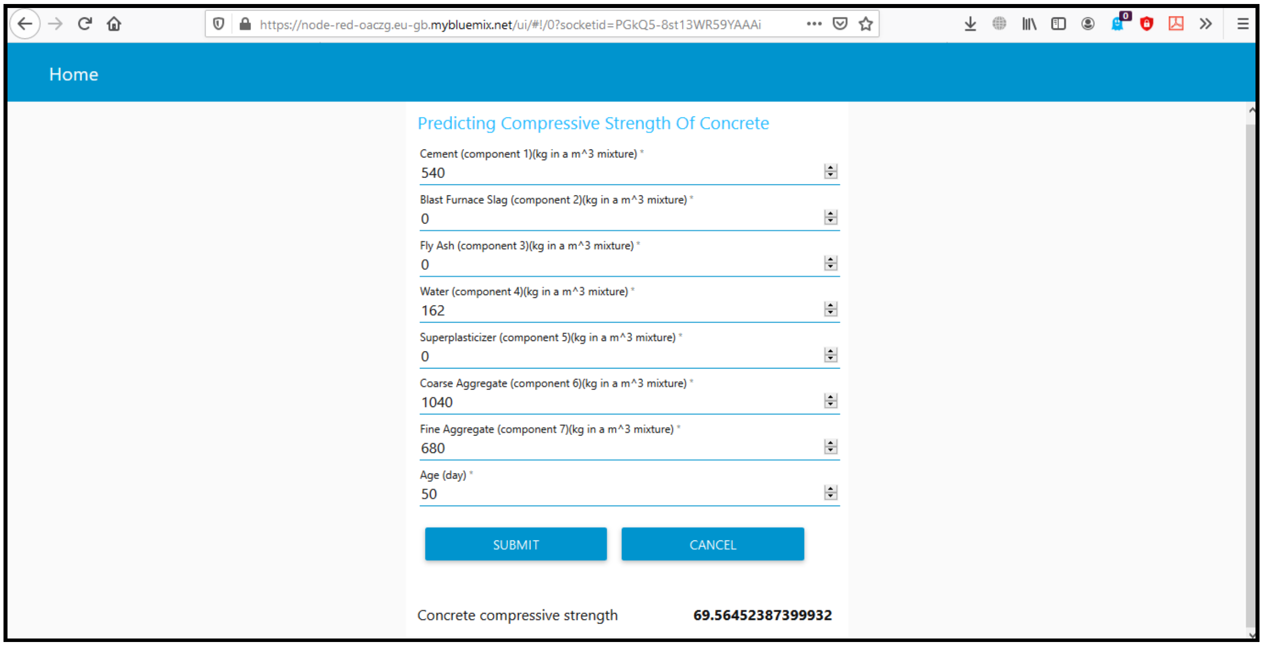
- **Creating Node Red Service :**



- **Building UI with Nodered :**



- **Output :**


https://node-red-oaczg.eu-gb.mybluemix.net/ui/#!/0?socketid=PGkQ5-8st13WR59YAAAi
Home
Predicting Compressive Strength Of Concrete
Cement (component 1)(kg in a m^3 mixture) *
540
Blast Furnace Slag (component 2)(kg in a m^3 mixture) *
0
Fly Ash (component 3)(kg in a m^3 mixture) *
0
Water (component 4)(kg in a m^3 mixture) *
162
Superplasticizer (component 5)(kg in a m^3 mixture) *
0
Coarse Aggregate (component 6)(kg in a m^3 mixture) *
1040
Fine Aggregate (component 7)(kg in a m^3 mixture) *
680
Age (day) *
50
SUBMIT
CANCEL
Concrete compressive strength
69.56452387399932