

**Q1 a) You are developing a machine-learning model for a prediction task. As you increase the complexity of your model, for example, by adding more features or by including higher-order polynomial terms in a regression model, what is most likely to occur? Explain in terms of bias and variance with suitable graphs as applicable.**

- Underfitting : When the model is too simple, it cannot capture the underlying patterns, leading to high bias and low variance. Both training and test errors are high.
- Optimal Complexity : There is a sweet spot where the model complexity is just right. The model captures the underlying patterns without fitting the noise.
- Overfitting : When the model is too complex , it captures the noise in the training data, leading to low bias but high variance. Training error is low, but test error is high.

**b)You're working at a tech company that has developed an advanced email**

**filtering system to ensure users' inboxes are free from spam while safeguarding legitimate messages. After the model has been trained, you are tasked with evaluating its performance on a validation dataset containing a mix of spam and legitimate emails. The results show that the model successfully identified 200 spam emails. However, 50 spam emails managed to slip through, being incorrectly classified as legitimate. Meanwhile, the system correctly recognised most of the legitimate emails, with 730 reaching the users' inboxes as intended. Unfortunately, the filter mistakenly flagged 20 legitimate emails as spam, wrongly diverting them to the spam folder. You are asked to assess the model by calculating an average of its overall classification performance across the different categories of emails.**

The performance of the email filtering system was evaluated using these metrics: Precision, Recall, F1-Score, and Accuracy. The results are as follows:

- Precision: 90.9%
- Recall: 80%
- F1-Score: 85.1%
- Accuracy: 93%

These metrics indicate that the system is highly effective at correctly identifying spam emails, with a precision of 90.9%, meaning that the majority of emails flagged as spam are indeed spam.

The recall of 80% shows that the model successfully identifies most spam emails, though we can still improve a bit.

The F1-Score of 85.1% gives a balanced measure of the system's performance, considering both precision and recall.

Finally, the overall accuracy of 93% demonstrates that the system correctly classifies the vast majority of emails.

At last we can say that the email filtering system performs well in maintaining a spam-free inbox.

c)

we know  $m$  can be calculated by

$$m = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2}$$

$$R^2 \rightarrow c = \frac{(\sum y)(\sum x^2) - (\sum x)(\sum xy)}{n(\sum x^2) - (\sum x)^2}$$

for  $n=12$

$$\sum x = 3 + 6 + 10 + 15 + 18 = 52$$

$$\sum y = 15 + 30 + 55 + 85 + 100 = 285$$

$$\sum xy = 45 + 180 + 550 + 1275 + 1800 = 3660$$

$$\sum x^2 = 3^2 + 6^2 + 10^2 + 15^2 + 18^2 = 529$$

$$m = \frac{5(3660) - 52(285)}{5(529) - 52^2} \approx 13.7$$

$$c = \frac{529 \cdot 285 - 3660 \cdot 52}{5 \cdot 529 - 52^2} \approx 670.92$$

$$y = (13.65)(12) + (670.92) \rightarrow \boxed{y \approx 834}$$

d)

$f_1$ : high degree polynomial regression model  
 $f_2$ : simple regression model (linear)

empirical risk

- \*  $f_1$ : very low empirical risk & can fit the data very well
- \*  $f_2$ : it is comparatively less flexible & cannot capture this quadratic data very well.

generalising the model

- \* although  $f_1$  fits the data perfectly, likely to overfit ( $f_1$ )
- \* as it doesn't work as good as  $f_2$  on training data we can say that it works better on generalised data set (bigger than training).

here the e.g. value of  $X$  &  $Y$  is taken to be

$X: \{1, 4, 9, 2, 3, 5, 6\}$

$Y: \{1, 16, 81, 4, 9, 25, 36\}$

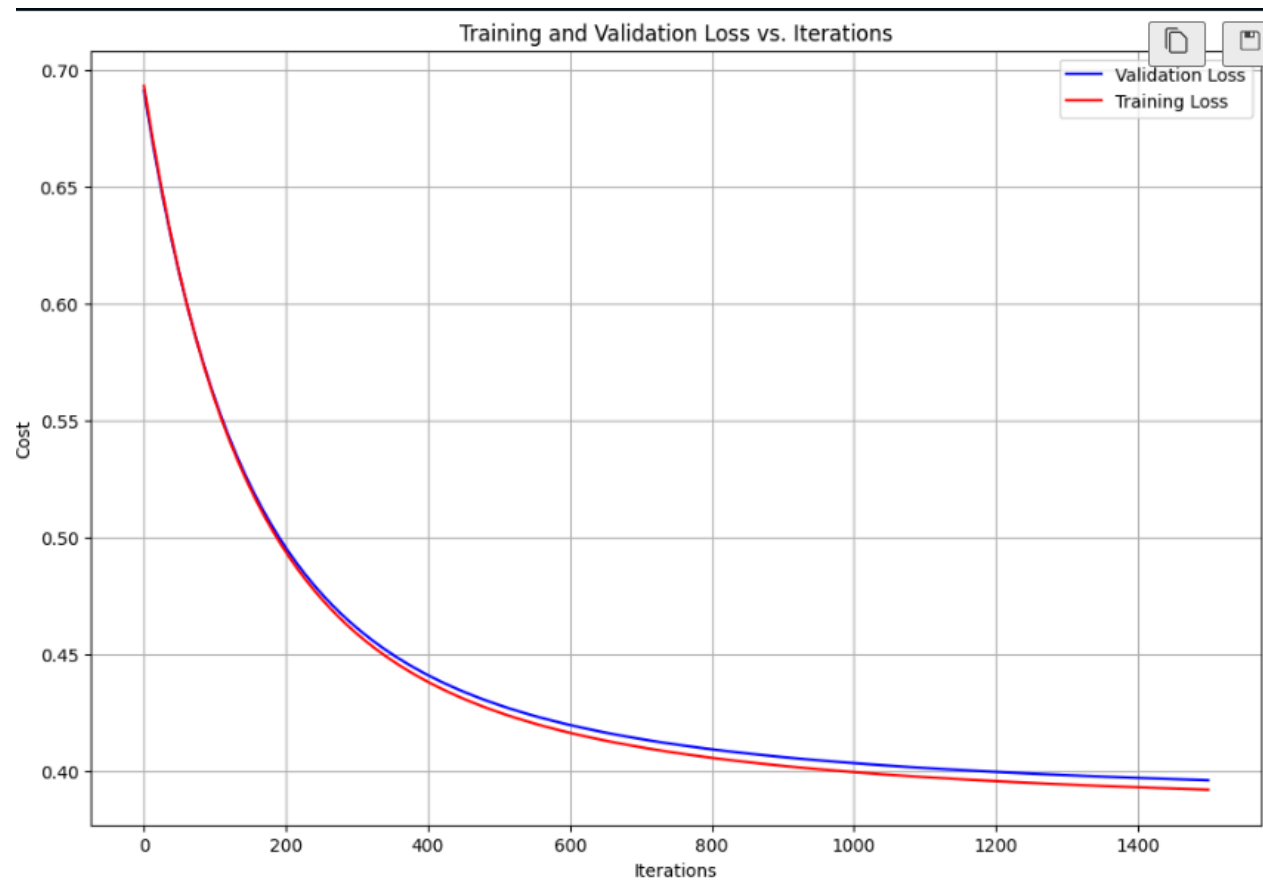
for testing

$X_{\text{test}} = \{4, 6\}$

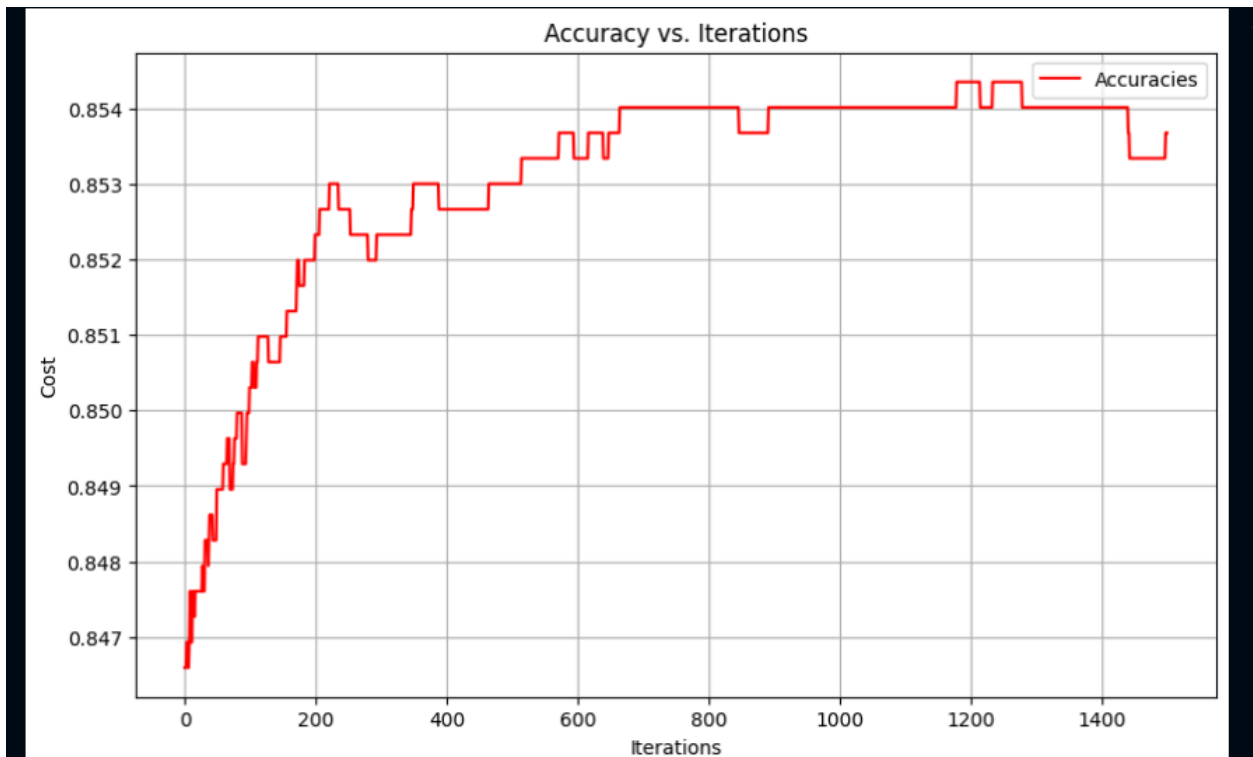
$Y_{\text{test}} = \{1, 1\}$

$f_1$  due to overfitting will not predict the correct values.

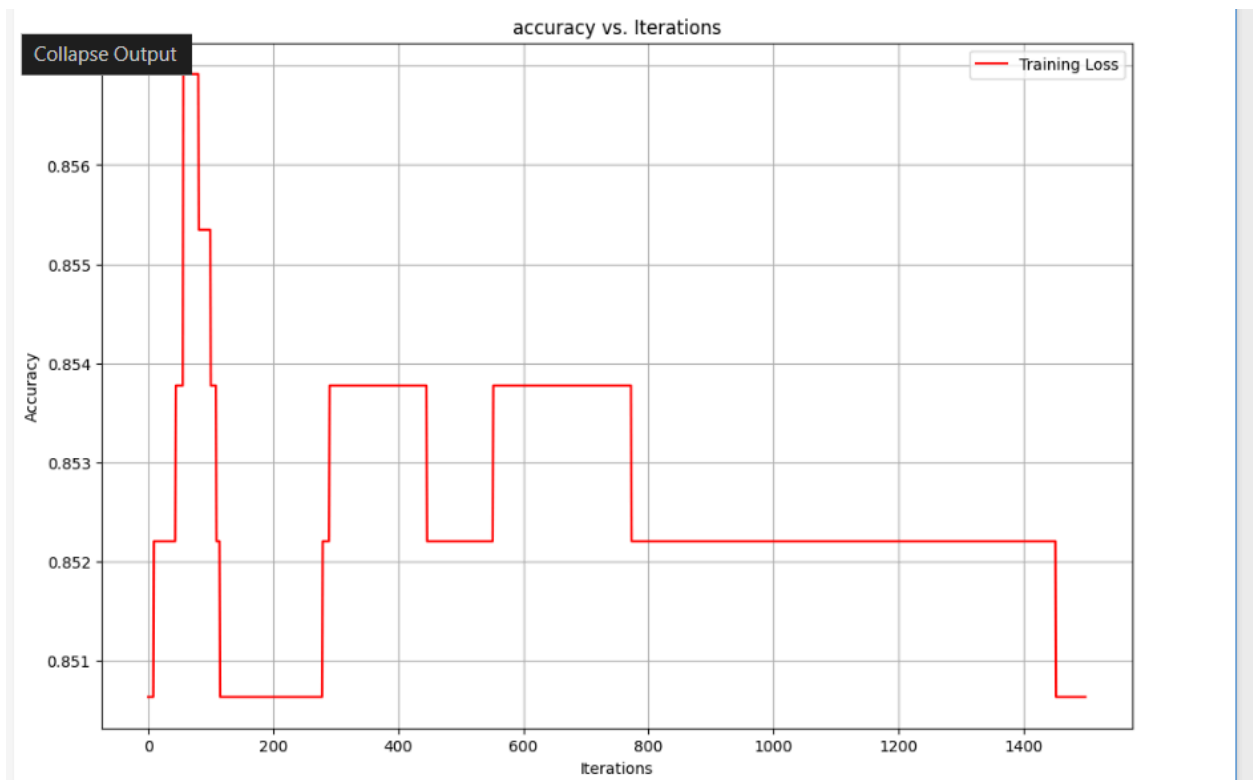
Q2:



On training:



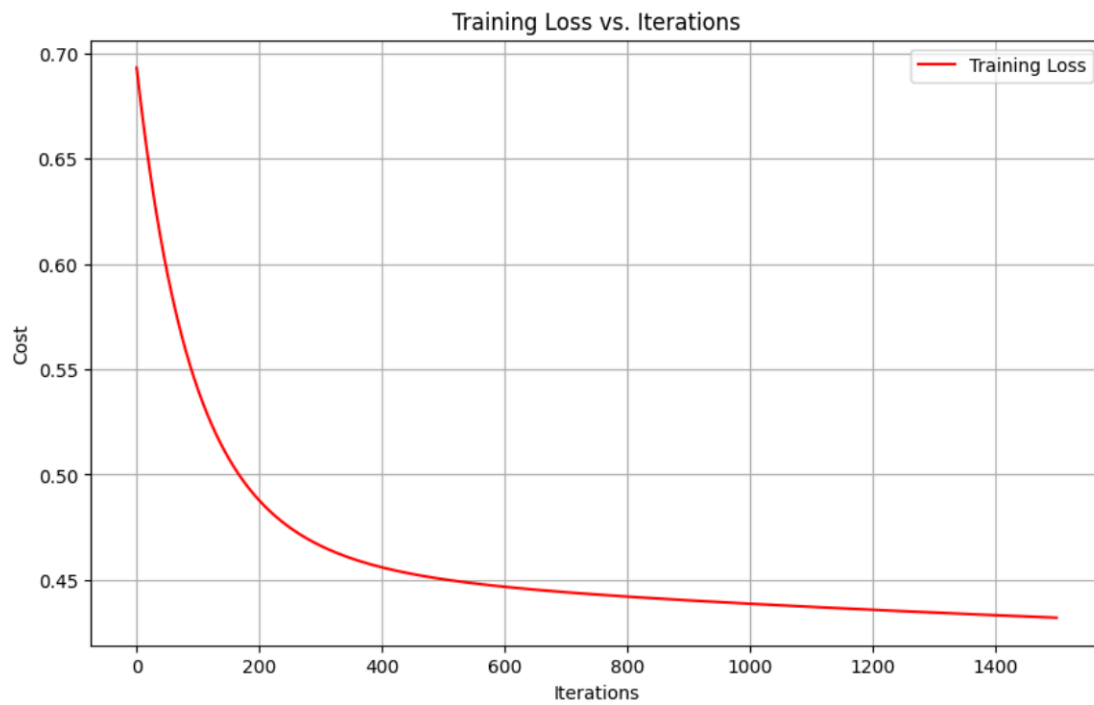
On validation :

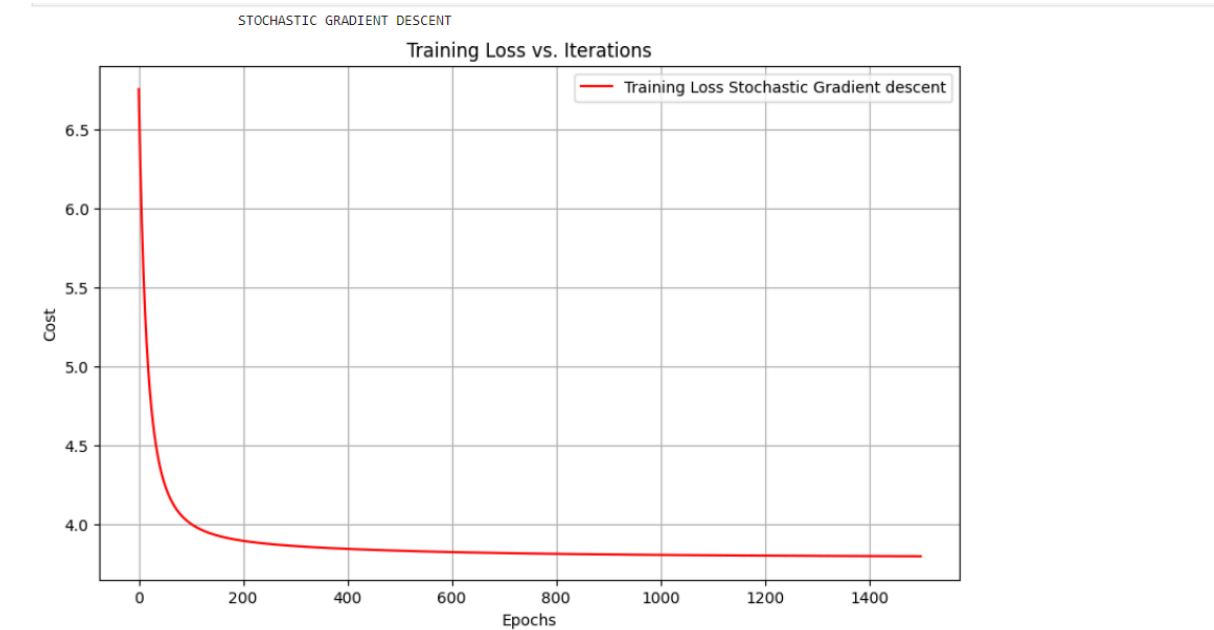
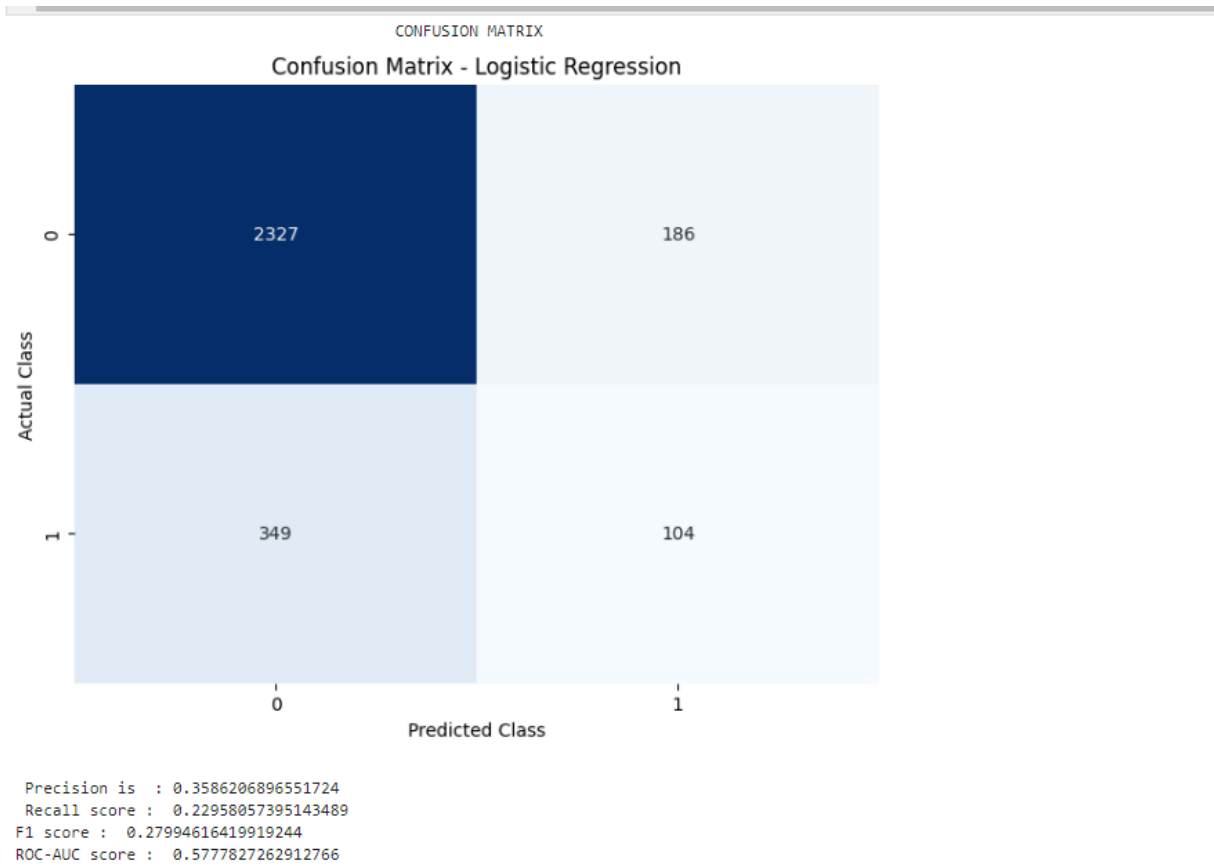


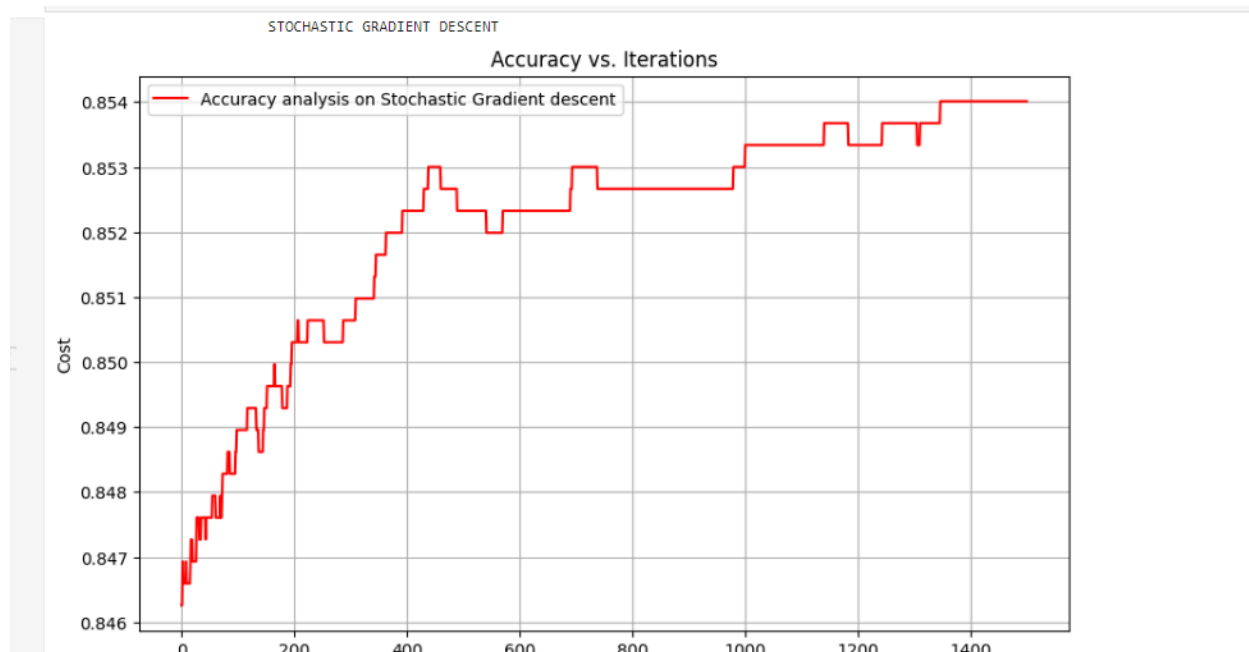
MIN MAX SCALING VS NO SCALING : LOSS VS ITERATION GRAPHS



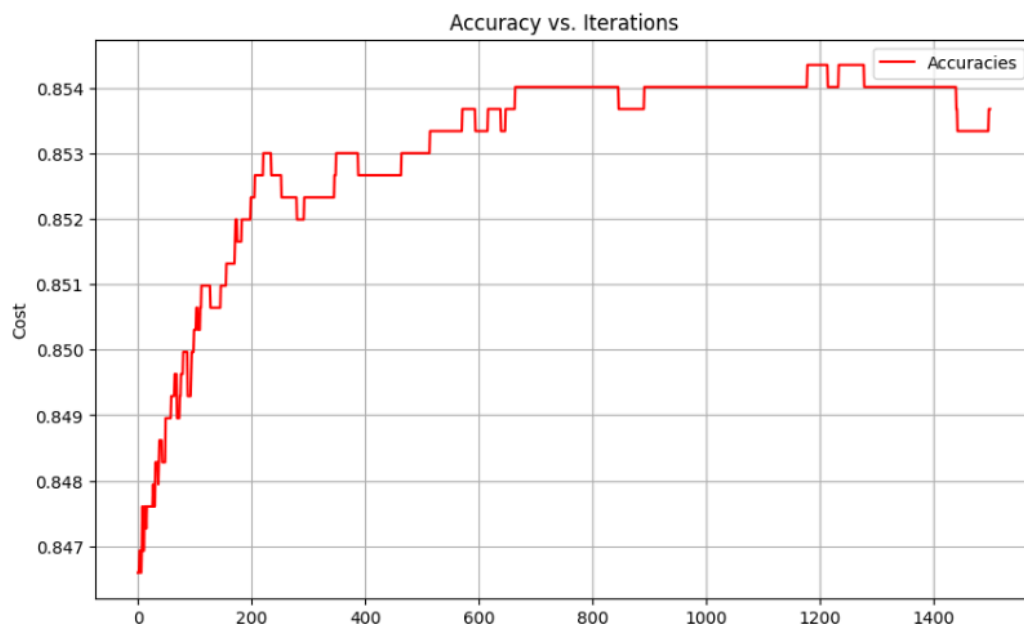
No scaling accuracy : 0.8569182389937107



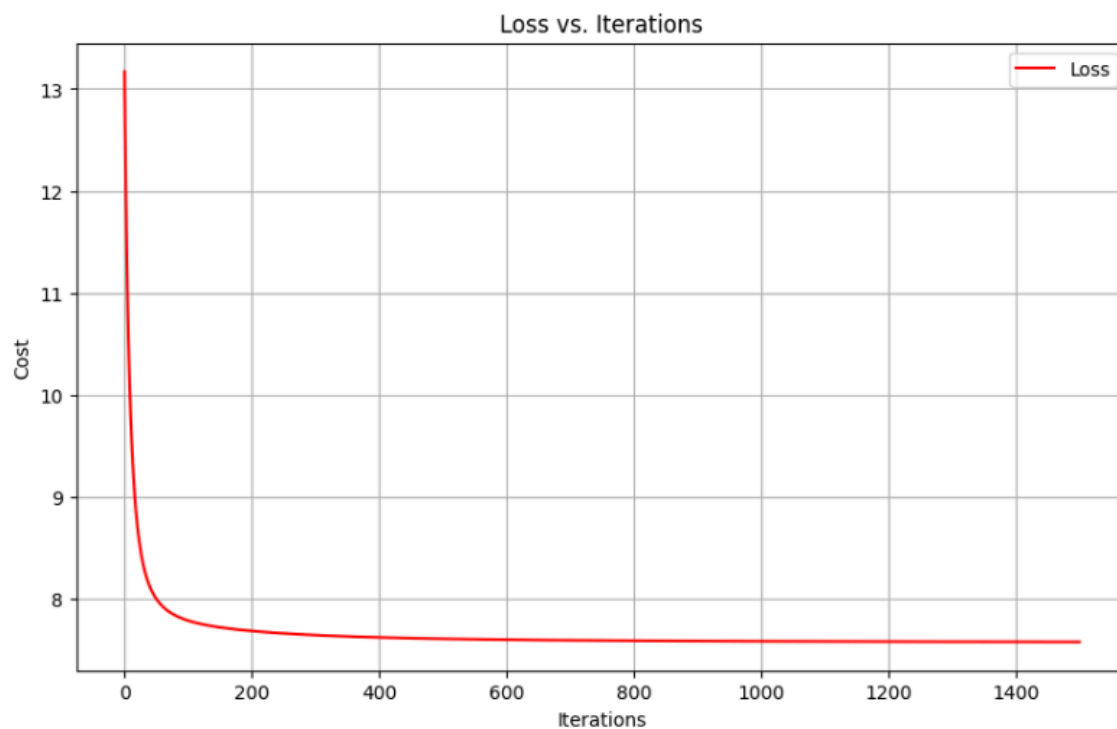




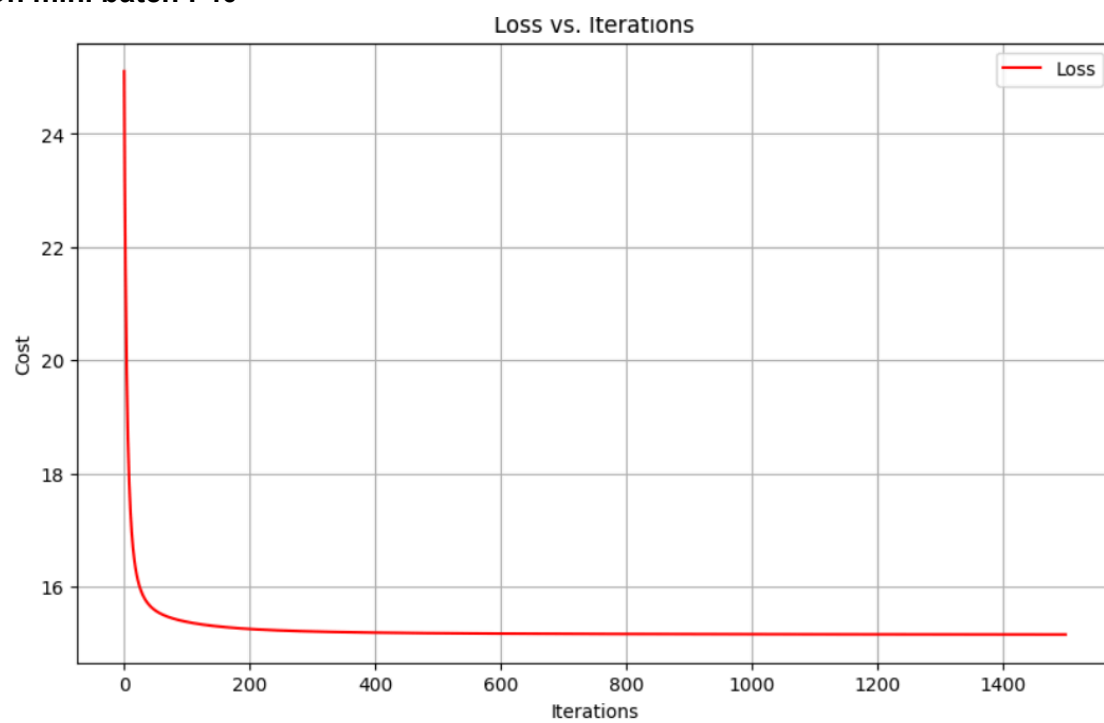
**On mini batch :**  
**Batch = 20**

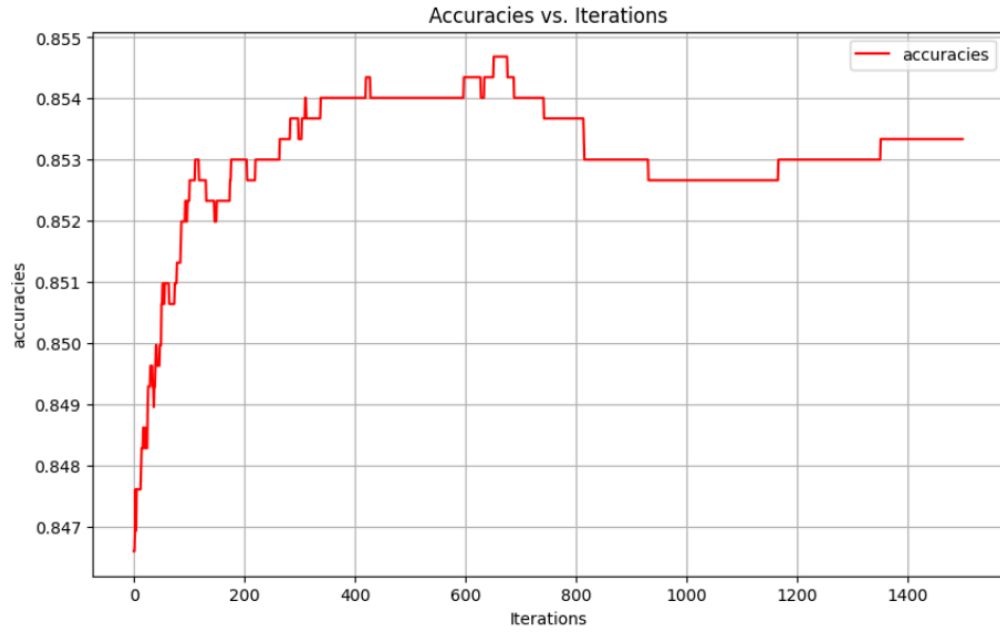






**On mini batch : 40**





**For k =5 , cross validation :**

#### K-Cross Validation

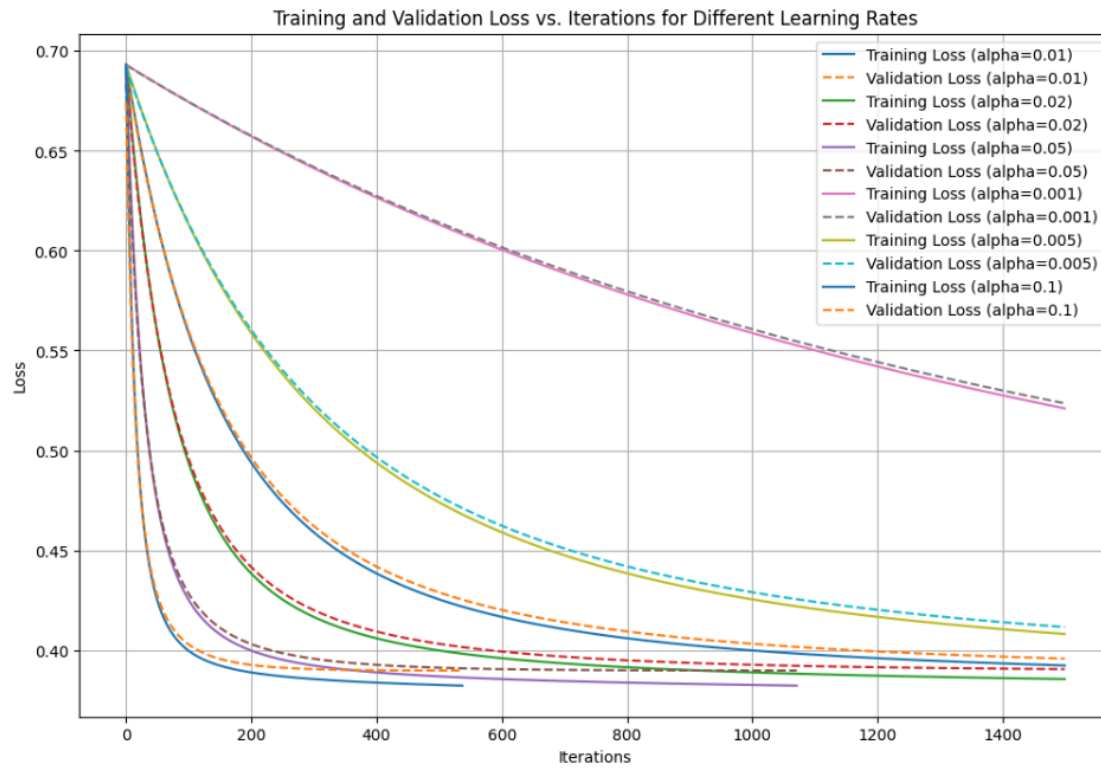
Mean of accuracy: 0.8462057335581786 standard deviation : 0.013716492011914175  
Mean of precisions: 0.5 standard deviation : 0.27386127875258304  
Mean of recalls: 0.026739433971546343 standard deviation : 0.008788911870554585  
Mean of f1\_score: 0.0503816199376947 standard deviation : 0.01674834984685916

## Early stopping with different learning rates :

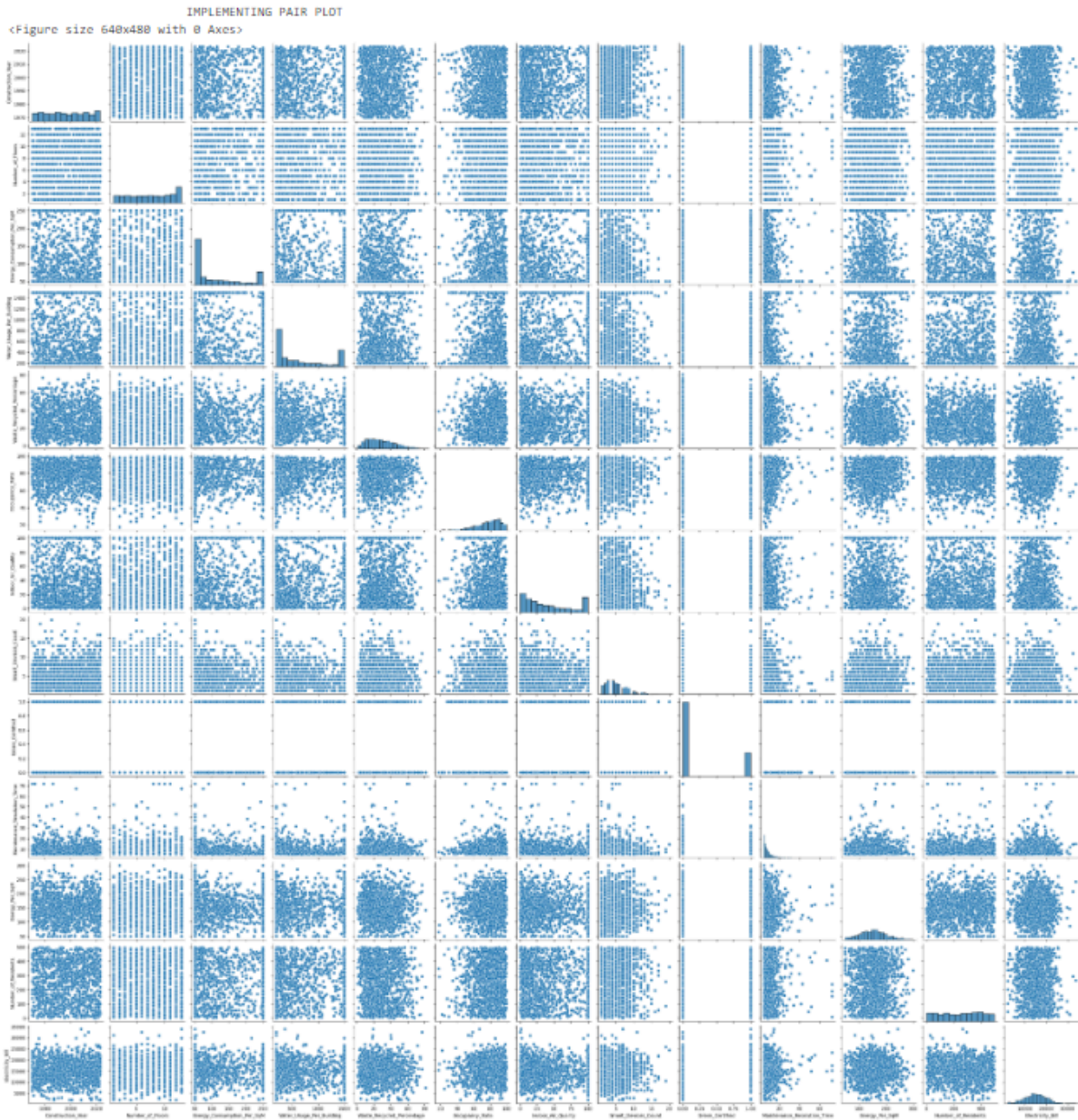
IMPLEMENTING EARLY STOP IN GRADIENT DESCENT

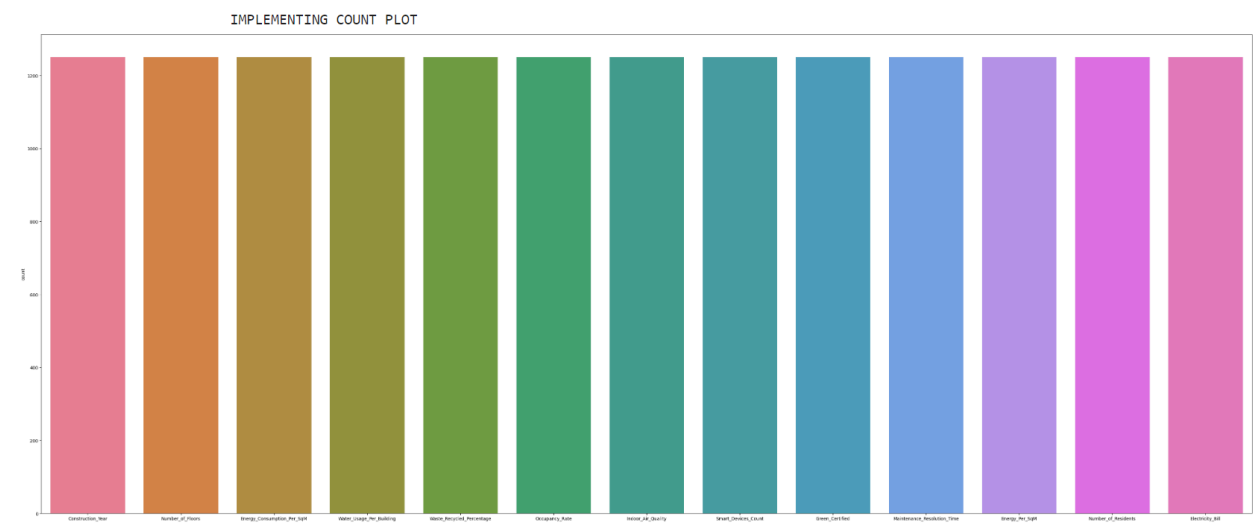
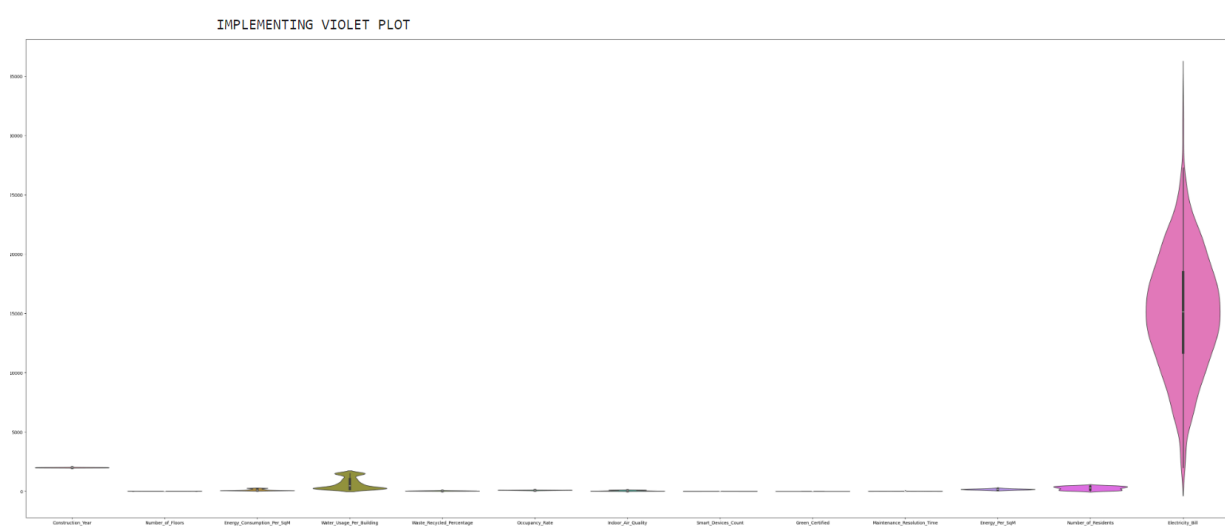
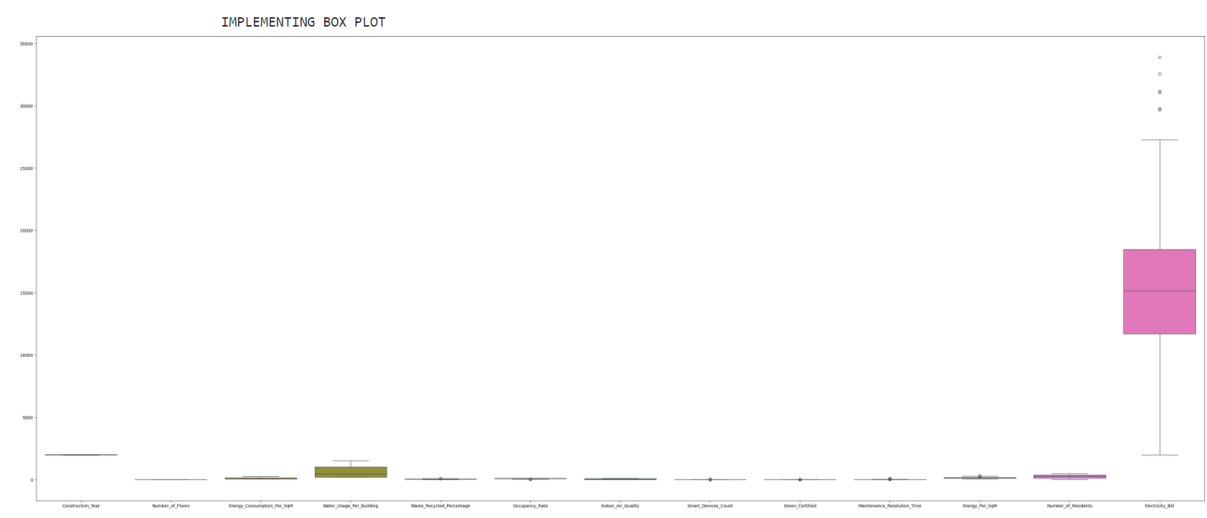
Early stop, patience exceeds 5 at iteration 1071

Early stop, patience exceeds 5 at iteration 537



## Section C:





#### LINEAR REGRESSION IMPLEMENTATION

```
Predictions: [14028.29588778 15485.78388992 14562.77957793 15403.56207339
16534.02545955]
Labels : [11586.96964, 7372.100374, 17605.19879, 3160.303673, 16951.74374]
mean squared error : 24730978.87656335
root mean squared error : 4973.025123258815
R2 score: 0.024262231392797706
adjusted R square value : 0.015228426395939021
mean absolute error : 4013.487414549532
```

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### Implemented rfse

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#### IMPLEMENTING RECURSIVE FEATURE ELIMINATION

Linear regression on 3 features only

```
mean squared error : 24730978.87656335
root mean squared error : 4973.025123258815
R2 score: 0.024262231392797706
adjusted R square value : 0.015228426395939021
mean absolute error : 4013.487414549532
```

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```
1. from sklearn.linear_model import Ridge
```

#### IMPLEMENTING RIDGE REGRESSION

```
R2 value is 0.040090229690335044
root mean squared error : 4871.851179963258
mean squared error : 23734933.919709392
mean absolute error : 3905.5822062999027
adjusted R square value : 0.031353135313531455
```

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## Implementing independent component analysis ICA

### ACCURACY ANALYSIS OF ICA

Components : 5

R2 value is 0.05899205066563529  
root mean squared error : 4823.6462825096205  
mean squared error : 23267563.45876888  
mean absolute error : 3852.779364638778  
adjusted R square value : 0.03135313531353123

Components : 4

R2 value is 0.031969988530254345  
root mean squared error : 4892.414203263112  
mean squared error : 23935716.736290626  
mean absolute error : 3914.8369053263605  
adjusted R square value : 0.03135313531353123

Components : 6

R2 value is 0.08862536834413115  
root mean squared error : 4747.087919892537  
mean squared error : 22534843.71918965  
mean absolute error : 3791.596891200691  
adjusted R square value : 0.03135313531353123

Components : 8

R2 value is 0.27855794313860704  
root mean squared error : 4223.568434931977  
mean squared error : 17838530.324553754  
mean absolute error : 3405.2455641533816  
adjusted R square value : 0.03135313531353123

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```
print('Gradient Boosting Regressor Metrics: ', get_metrics())
```

#### ELASTICNET REGULARIZATION

ElasticNet with alpha=0.1  
ElasticNet Coefficients: [-188.05334957 -194.7530676 250.0206893 149.62509516 -84.20088495  
84.56093749 -164.31000627 1026.71689113 163.71320324 -194.69104001  
220.5003022 -199.86776472 39.37244414 160.17034823 101.81470526]  
ElasticNet Intercept: 14758.796183976001  
Evaluation on test set:  
MSE: 20508488.89608697  
RMSE: 4528.629913791474  
MAE: 3618.572646802898  
R<sup>2</sup>: 0.07246248211724537  
Adjusted R<sup>2</sup>: 0.013004948919632997

ElasticNet with alpha=0.5  
ElasticNet Coefficients: [-132.55342793 -155.97143848 192.66355021 125.4147739 -27.64467219  
37.85129546 -121.54855902 750.90073435 109.26283983 -142.66845703  
164.51953988 -138.57865253 23.55073421 129.45768849 59.79540689]  
ElasticNet Intercept: 14758.796183976001  
Evaluation on test set:  
MSE: 20669973.915639374  
RMSE: 4546.42430000977  
MAE: 3629.495658462251  
R<sup>2</sup>: 0.06515899842472106  
Adjusted R<sup>2</sup>: 0.005233293195536559

ElasticNet with alpha=1.0  
ElasticNet Coefficients: [-97.06805171 -123.5500937 150.31428296 102.87676612 -2.82325032  
16.58464225 -91.62093686 564.79056227 77.15229828 -106.4330244  
125.71581541 -99.76328586 13.84536472 103.97680504 36.75932753]  
ElasticNet Intercept: 14758.796183976001  
Evaluation on test set:  
MSE: 20884815.71133026  
RMSE: 4569.990778035582  
MAE: 3646.892010577539  
R<sup>2</sup>: 0.055442347582121854  
Adjusted R<sup>2</sup>: -0.005106219880562701

ElasticNet with alpha=5.0  
ElasticNet Coefficients: [-31.02134617 -45.43071145 54.87150212 41.09037866 11.57462869  
-1.93402607 -30.74166746 191.60246902 23.07165486 -34.56602991  
44.35256501 -30.26655203 0.95897541 40.01359262 6.23290908]  
ElasticNet Intercept: 14758.796183976001  
Evaluation on test set:  
MSE: 21591219.97389798  
RMSE: 4646.635339027367  
MAE: 3708.5851760396854  
R<sup>2</sup>: 0.023493798879010153  
Adjusted R<sup>2</sup>: -0.03910275247489947