## **Question 5**

**Max accuracy** was achieved when I used the following hyperparameters:

```
• n estimators=700
```

• min samples leaf=2

• max\_depth=4

• max features=None

• learning rate=0.1

## For **best** implementation:

Accuracy: 0.9974782852339591 Precision: 0.997039230199852

Recall: 1.0

As no of trees increases, all three (accuracy, precision, recall) seem to improve. Gradient boosting is robust to overfitting, and hence, it performs better as we increase n\_estimators.

```
For n estimators=100:
```

Accuracy: 0.9948164752031381 Precision: 0.9940949725252194 Recall: 0.9998350243339107

For n\_estimators=300:

Accuracy: 0.9965676660128888 Precision: 0.996137409598948 Recall: 0.9998350243339107

For n\_estimators=500:

Accuracy: 0.997128047072009 Precision: 0.9967927631578948 Recall: 0.9998350243339107

## For $n_{estimators=700$ :

Accuracy: 0.997338189969179
Precision: 0.9969569865942923
Recall: 0.9999175121669553

## For a **simple decision tree** implementation:

Accuracy: 0.9912440459512468
Precision: 0.9952121512299819

Recall: 0.99447331518601

Clearly, gradient boosting is much better than a simple decision tree in terms of accuracy. Precision, recall too, are better for boosting method.