In [ ]:
```
# Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

The power system consists of 4 generators of 11 × 10^3 V, each pair located at each end of the transmission line. Transformers are present in between to simulate and study the various faults at the midpoint of the transmission line.

What are Electrical Faults?

Normally, a power system operates under balanced conditions. When the system becomes unbalanced due to the failures of insulation at any point or due to the contact of live wires, a short–circuit or fault, is said to occur in the line. Faults may occur in the power system due to the number of reasons like natural disturbances (lightning, high-speed winds, earthquakes), insulation breakdown, falling of a tree, bird shorting, etc.

Faults can be brodly categorised into two types:

1. Open-circuit Fault
2. Short-Circuit Faults

Short-Circuit Faults

1. Symmetrical
2. Asymmetrical Faults

Symmetrical and Asymmetrical Faults

Symmetrical Faults In symmetrical faults, all phases are shorted to each other or to earth (L-L-L) or (L-L-L-G). The nature of this type of fault is balanced. In this type of fault,fault currents in all phases are symmetrical i.e. their magnitudes are equal and they are equally displaced by angle 120 degree. It is more severe type of fault but it occurs rarely.

Asymmetrical Faults These faults involve only one or two phases. In this type of fault, three phase lines become unbalanced. There are mainly three types namely line to ground (L-G), line to line (L-L) and double line to ground (LL-G) faults. These type of faults mostly occur on power system..

This file contains the dataset to classify the types of fault.

Inputs - [Ia,Ib,Ic,Va,Vb,Vc] Ia = Current in line A

Ib = Current in line B

Ic = Current in line C

Va = Voltage in line A

Vb = Voltage in line B

Vc = Voltage in line C

Examples :

[G C B A] - Outputs

[0 0 0 0] - No Fault

[1 0 0 0] - Ground Fault

[0 0 0 1] - Fault in Line A

[0 0 1 0] - Fault in Line B

[0 1 0 0] - Fault in Line C

[1 0 0 1] - LG fault (Between Phase A and Ground)

[1 0 1 0] - LG fault (Between Phase B and Ground)

[1 1 0 0] - LG fault (Between Phase C and Ground)

[0 0 1 1] - LL fault (Between Phase B and Phase A)

[0 1 1 0] - LL fault (Between Phase C and Phase B)

[0 1 0 1] - LL fault (Between Phase C and Phase A)

[1 1 0 0] - LG fault (Between Phase C and Ground)

[1 0 1 0] - LG fault (Between Phase B and Ground)

[1 0 0 1] - LG fault (Between Phase A and Ground)

[1 0 1 1] - LLG Fault (Between Phases A,B and Ground)

[1 1 0 1] - LLG Fault (Between Phases A,C and Ground)

[1 1 1 0] - LLG Fault (Between Phases C,B and Ground)

[0 1 1 1] - LLL Fault(Between all three phases)

[1 1 1 1] - LLLG fault(Three phase symmetrical fault)

In [ ]:
```
power_df = pd.read_csv('classData.csv')
power_df.head()
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc
0	1	0	0	1	-151.291812	-9.677452	85.800162	0.400750	-0.132935	-0.267815
1	1	0	0	1	-336.186183	-76.283262	18.328897	0.312732	-0.123633	-0.189099
2	1	0	0	1	-502.891583	-174.648023	-80.924663	0.265728	-0.114301	-0.151428
3	1	0	0	1	-593.941905	-217.703359	-124.891924	0.235511	-0.104940	-0.130570
4	1	0	0	1	-643.663617	-224.159427	-132.282815	0.209537	-0.095554	-0.113983

Voltage is in Per Unit value (pu)

If there is any confusion regarding the values of the Line voltages, then let it be clarify that they are most probably in p.u. value i.e.

Vp.u.=V/Vbase

In actual the power system consists of 4 generators of 11 × 10^3 V. so we can convert by multiplying them by Volts provided they have taken 11k as their base

In [ ]:
```
power_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7861 entries, 0 to 7860
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   G       7861 non-null   int64  
 1   C       7861 non-null   int64  
 2   B       7861 non-null   int64  
 3   A       7861 non-null   int64  
 4   Ia      7861 non-null   float64
 5   Ib      7861 non-null   float64
 6   Ic      7861 non-null   float64
 7   Va      7861 non-null   float64
 8   Vb      7861 non-null   float64
 9   Vc      7861 non-null   float64
dtypes: float64(6), int64(4)
memory usage: 614.3 KB
```

In [ ]:
```
# Checking for null values
power_df.isnull().sum()
```

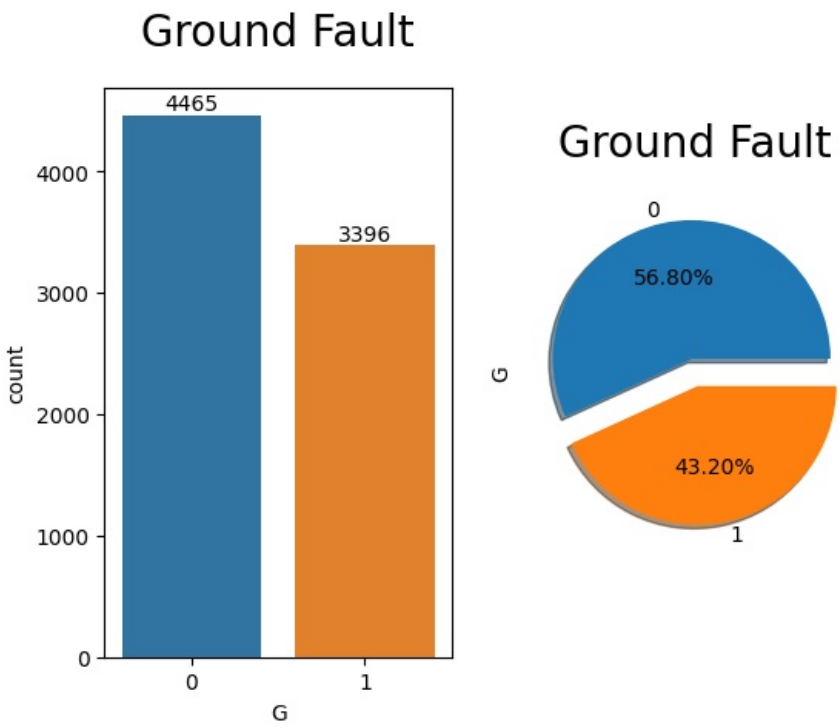
Out[ ]:
```
G     0
C     0
B     0
A     0
Ia    0
Ib    0
Ic    0
Va    0
Vb    0
Vc    0
dtype: int64
```

In [ ]:
```
power_df.shape
```

Out[ ]: (7861, 10)

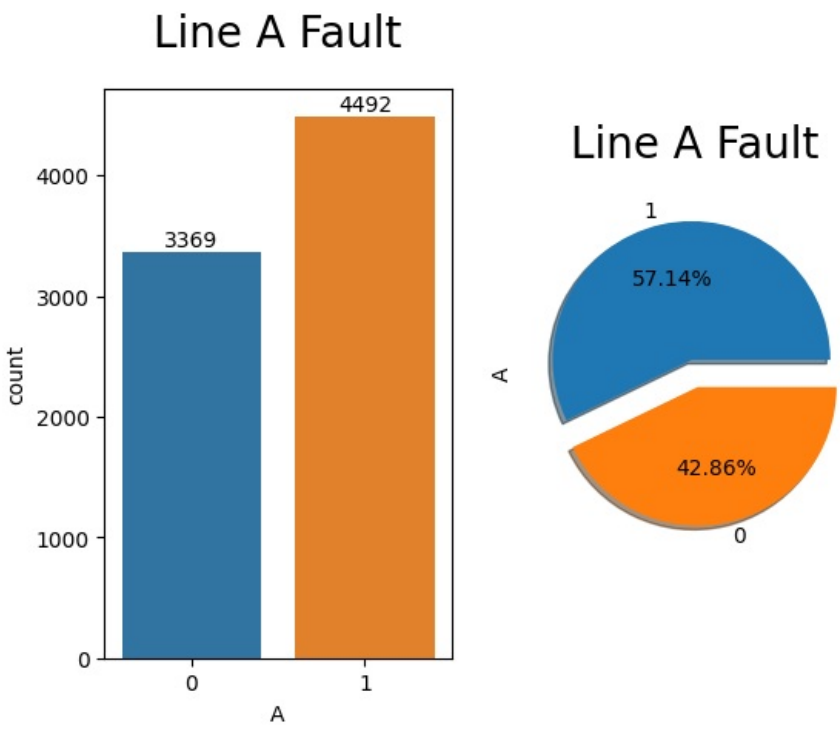
In [ ]:
```
ax = plt.subplot(1,2,1)
ax = sns.countplot(x = 'G' , data = power_df)
ax.bar_label(ax.containers[0])
plt.title('Ground Fault' ,fontsize = 20 ,pad = 20)

ax = plt.subplot(1,2,2)
ax = power_df['G'].value_counts().plot.pie(explode = [0.1,0.1] ,
                                           autopct = '%1.2f%%' , shadow = True)
plt.title('Ground Fault' ,fontsize = 20 ,pad = 20)
```

Out[ ]: Text(0.5, 1.0, 'Ground Fault')



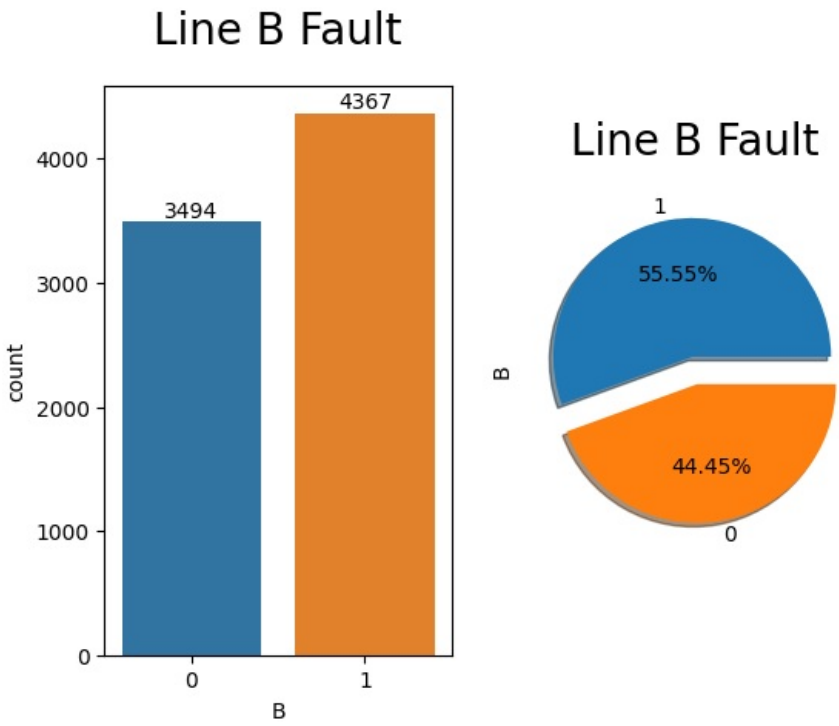
In [ ]:
```
ax = plt.subplot(1,2,1)
ax = sns.countplot(x = 'A' , data = power_df)
ax.bar_label(ax.containers[0])
plt.title('Line A Fault' ,fontsize = 20 ,pad = 20)

ax = plt.subplot(1,2,2)
ax = power_df['A'].value_counts().plot.pie(explode = [0.1,0.1] ,
                                           autopct = '%1.2f%%' , shadow = True)
plt.title('Line A Fault' ,fontsize = 20 ,pad = 20)
```

Out[ ]: Text(0.5, 1.0, 'Line A Fault')



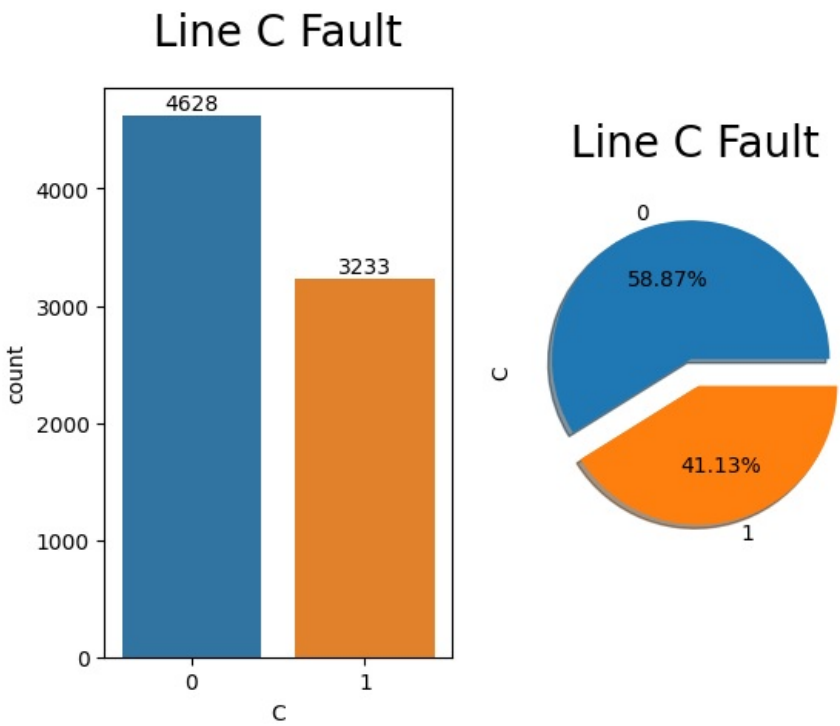
In [ ]:
```
ax = plt.subplot(1,2,1)
ax = sns.countplot(x = 'B' , data = power_df)
ax.bar_label(ax.containers[0])
plt.title('Line B Fault' ,fontsize = 20 ,pad = 20)

ax = plt.subplot(1,2,2)
ax = power_df['B'].value_counts().plot.pie(explode = [0.1,0.1] ,
                                           autopct = '%1.2f%%' , shadow = True)
plt.title('Line B Fault' ,fontsize = 20 ,pad = 20)
```

Out[ ]:
```
Text(0.5, 1.0, 'Line B Fault')
```



In [ ]:
```
ax = plt.subplot(1,2,1)
ax = sns.countplot(x = 'C' , data = power_df)
ax.bar_label(ax.containers[0])
plt.title('Line C Fault' ,fontsize = 20 ,pad = 20)

ax = plt.subplot(1,2,2)
ax = power_df['C'].value_counts().plot.pie(explode = [0.1,0.1] ,
                                           autopct = '%1.2f%%' , shadow = True)
plt.title('Line C Fault' ,fontsize = 20 ,pad = 20)
```

Out[ ]:
```
Text(0.5, 1.0, 'Line C Fault')
```



Combining all fault together in one Fault_type

Combining all fault together in one Fault_type

In [ ]:
```
power_df['Fault_Type'] = (power_df['G'].astype('str')+ power_df['C'].astype('str')+
                          power_df['B'].astype('str')+power_df['A'].astype('str'))
power_df.head()
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
0	1	0	0	1	-151.291812	-9.677452	85.800162	0.400750	-0.132935	-0.267815	1001
1	1	0	0	1	-336.186183	-76.283262	18.328897	0.312732	-0.123633	-0.189099	1001
2	1	0	0	1	-502.891583	-174.648023	-80.924663	0.265728	-0.114301	-0.151428	1001
3	1	0	0	1	-593.941905	-217.703359	-124.891924	0.235511	-0.104940	-0.130570	1001
4	1	0	0	1	-643.663617	-224.159427	-132.282815	0.209537	-0.095554	-0.113983	1001

In [ ]:
```
def imputepropername(column):
    if column == '0000':
        return 'NO Fault'
    elif column == '1001':
        return 'Line A to Ground Fault'
    elif column == '0110':
        return 'Line B to Line C Fault'
    elif column == '1011':
        return 'Line A Line B to GroundFault'
    elif column == '0111':
        return 'Line A  Line B  Line C Fault'
    else:
        return 'Line A Line B Line C to Ground Fault'
```

Giving the proper name to the fault according to the data description

In [ ]:
```
# power_df['Fault_Type'][power_df['Fault_Type'] == '0000' ] = 'NO Fault'
# power_df['Fault_Type'][power_df['Fault_Type'] == '1001' ] = 'Line A to Ground Fault'
# power_df['Fault_Type'][power_df['Fault_Type'] == '0110' ] = 'Line B to Line C Fault'
# power_df['Fault_Type'][power_df['Fault_Type'] == '1011' ] = 'Line A Line B to Ground Fault'
# power_df['Fault_Type'][power_df['Fault_Type'] == '0111' ] = 'Line A Line B Line C'
# power_df['Fault_Type'][power_df['Fault_Type'] == '1111' ] = 'Line A Line B Line C to Ground Fault'
```

In [ ]:
```
power_df['Fault_Type'] = power_df['Fault_Type'].apply(imputepropername)
```

In [ ]:
```
power_df['Fault_Type'].unique()
```

Out[ ]:
```
array(['Line A to Ground Fault', 'Line A Line B to GroundFault',
       'Line B to Line C Fault', 'Line A  Line B  Line C Fault',
       'Line A Line B Line C to Ground Fault', 'NO Fault'], dtype=object)
```

In [ ]:
```
power_df.sample(10)
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
2204	1	0	1	1	723.870492	34.590221	41.201471	0.057548	-0.390981	0.333433	Line A Line B to GroundFault
4170	0	1	1	1	-446.384881	-435.962156	884.356094	-0.042326	0.022944	0.019382	Line A Line B Line C Fault
2228	1	0	1	1	497.570546	11.627588	32.690138	0.254039	-0.555656	0.301617	Line A Line B to GroundFault
791	1	0	0	1	-662.409780	-70.772699	31.410239	0.292641	-0.214903	-0.077738	Line A to Ground Fault
2548	0	1	1	0	-57.428337	723.166768	-663.187105	-0.043975	-0.019466	0.063441	Line B to Line C Fault
1975	1	0	1	1	-862.124165	338.813919	-21.382195	-0.024869	0.325030	-0.300161	Line A Line B to GroundFault
4885	1	1	1	1	-203.196547	-643.310095	846.504388	-0.041061	0.011471	0.029589	Line A Line B Line C to Ground Fault
7035	0	0	0	0	-71.548191	60.846947	7.597097	-0.105526	-0.453115	0.558641	NO Fault
6921	0	0	0	0	1.645907	82.212114	-86.996362	-0.577495	0.492848	0.084647	NO Fault
607	1	0	0	1	784.835736	68.165707	-20.771604	-0.222091	0.067262	0.154828	Line A to Ground Fault

In [ ]:
```
power_df.describe().style.background_gradient(cmap='rainbow').set_precision(3)
```

Out[ ]:

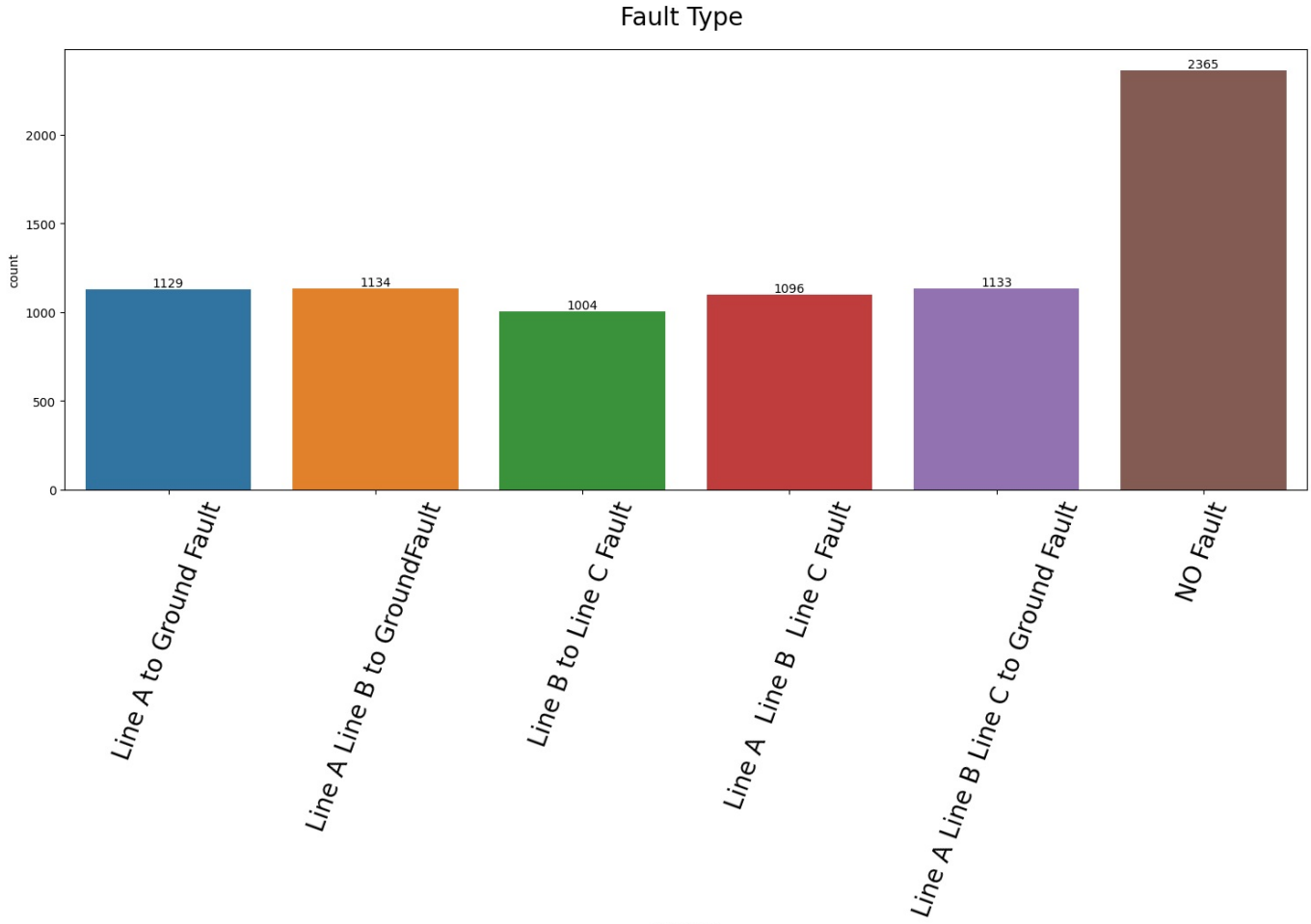
	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc
count	7861.000	7861.000	7861.000	7861.000	7861.000	7861.000	7861.000	7861.000	7861.000	7861.000
mean	0.432	0.411	0.556	0.571	13.721	-44.845	34.392	-0.008	0.001	0.007
std	0.495	0.492	0.497	0.495	464.742	439.269	371.107	0.289	0.313	0.308
min	0.000	0.000	0.000	0.000	-883.542	-900.527	-883.358	-0.621	-0.608	-0.613
25%	0.000	0.000	0.000	0.000	-119.803	-271.846	-61.034	-0.130	-0.160	-0.216
50%	0.000	0.000	1.000	1.000	2.043	5.513	-4.327	-0.005	0.002	0.009
75%	1.000	1.000	1.000	1.000	227.246	91.194	49.115	0.112	0.154	0.240
max	1.000	1.000	1.000	1.000	885.739	889.869	901.274	0.595	0.628	0.600

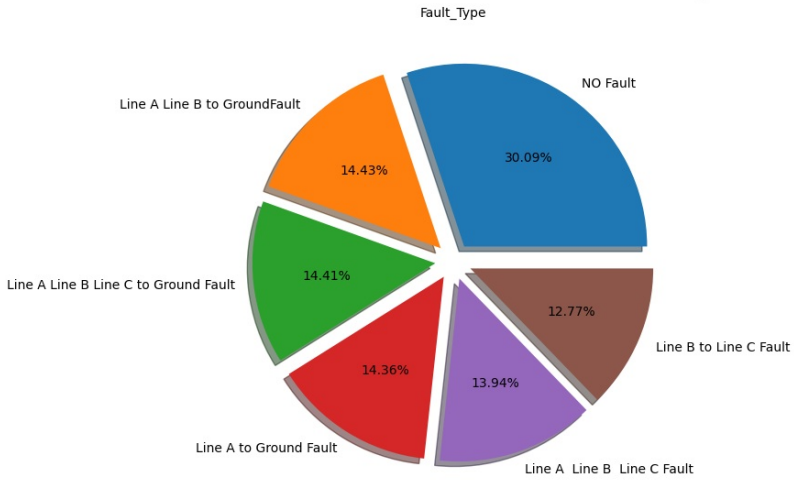
Counting Fault Types

In [ ]:
```
power_df['Fault_Type'].value_counts(ascending= False)
```

Out[ ]:
```
NO Fault                                2365
Line A Line B to GroundFault            1134
Line A Line B Line C to Ground Fault    1133
Line A to Ground Fault                  1129
Line A  Line B  Line C Fault            1096
Line B to Line C Fault                  1004
Name: Fault_Type, dtype: int64
```

In [ ]:
```
ax = plt.figure(figsize = (15,16))
ax = plt.subplot(2,1,1)
ax = sns.countplot(x = 'Fault_Type' , data = power_df)
ax.bar_label(ax.containers[0])
plt.title("Fault Type " , fontsize = 20 , pad =20)
plt.xticks(rotation =70 ,fontsize = 20)
plt.tight_layout()

ax = plt.subplot(2,1,2)
ax = power_df['Fault_Type'].value_counts().plot.pie(explode = [0.1,0.1,0.1,0.1, 0.1,0.1],
                                                    autopct = '%1.2f%%' ,shadow =True)
plt.tight_layout()
plt.axis('off');
```

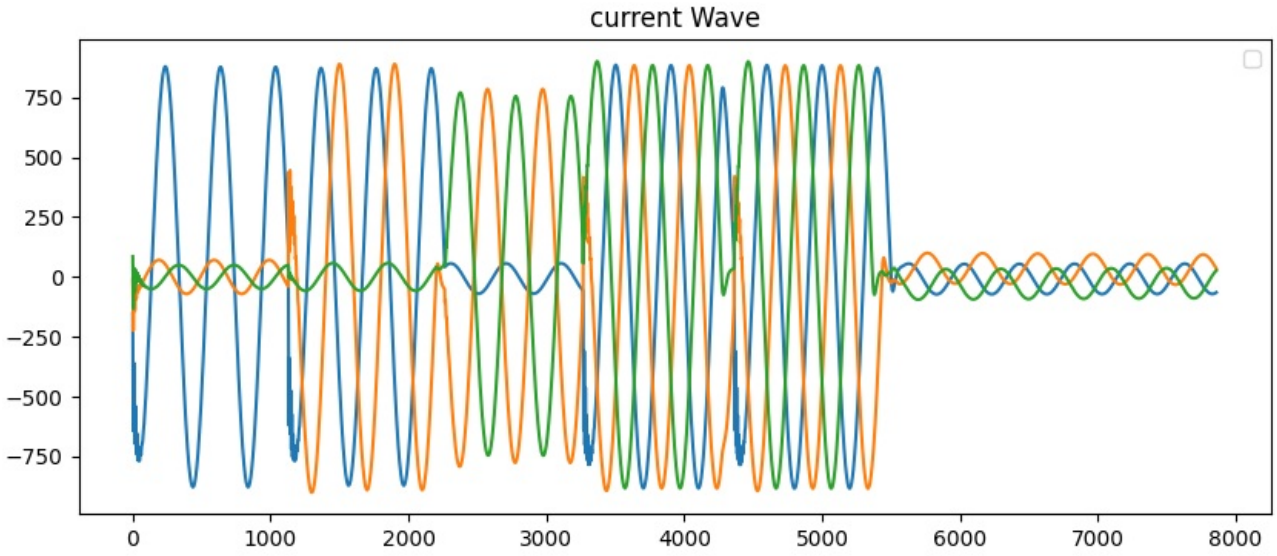




In [ ]:
```
plt.figure(figsize=(10,4))
plt.plot(power_df["Ia"])
plt.plot(power_df["Ib"])
plt.plot(power_df["Ic"])
plt.title('current Wave')
plt.legend()
```

```
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignor
ed when legend() is called with no argument.
```

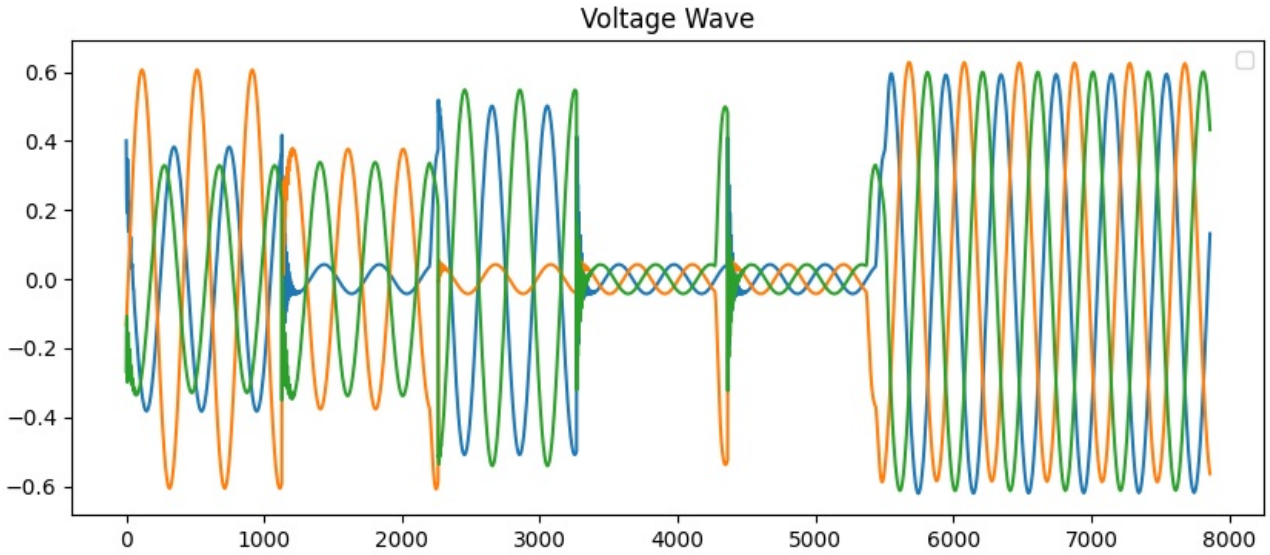
Out[ ]: <matplotlib.legend.Legend at 0x157863b1990>



In [ ]:
```
plt.figure(figsize=(10,4))
plt.plot(power_df["Va"])
plt.plot(power_df["Vb"])
plt.plot(power_df["Vc"])
plt.title('Voltage Wave')
plt.legend()
```

```
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignor
ed when legend() is called with no argument.
```

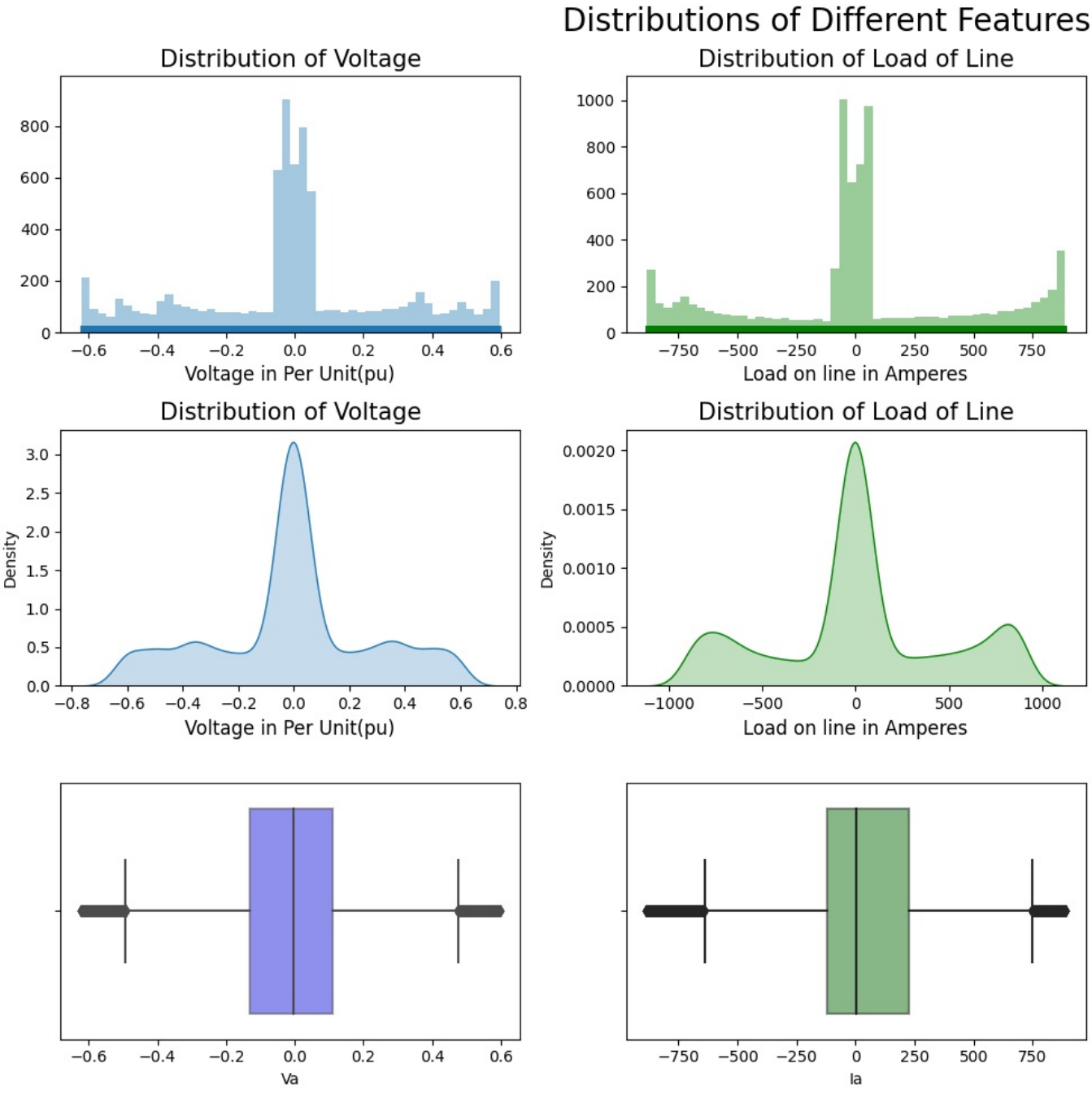
Out[ ]:
```
<matplotlib.legend.Legend at 0x15786f0c050>
```



Voltage or Current graph , where there is large fluctuations in the graph there faults have occured

In [ ]:
```
plt.figure(figsize= (15,10))
plt.suptitle("Distributions of Different Features", fontsize = 20)
#Histograms
plt.subplot(3,3,1)
sns.distplot(power_df['Va'], rug = True, kde = False)
plt.xlabel('Voltage in Per Unit(pu)', fontsize = 12)
plt.title('Distribution of Voltage',fontsize = 15)
```

```
plt.subplot(3,3,2)
sns.distplot(power_df['Ia'], color= 'green',rug = True, kde = False)
plt.title('Distribution of Load of Line',fontsize = 15)
plt.xlabel('Load on line in Amperes', fontsize = 12)


#Kde Plots
plt.subplot(3,3,4)
sns.kdeplot(power_df['Va'], shade = True)
plt.xlabel('Voltage in Per Unit(pu)', fontsize = 12)
plt.title('Distribution of Voltage',fontsize = 15)

plt.subplot(3,3,5)
sns.kdeplot(power_df['Ia'], shade = True, color = 'g')
plt.title('Distribution of Load of Line',fontsize = 15)
plt.xlabel('Load on line in Amperes', fontsize = 12)


#Box Plots
plt.subplot(3,3,7)
sns.boxplot(x = power_df['Va'], orient = 'v',color= 'b', boxprops=dict(alpha=.5))
plt.subplot(3,3,8)
sns.boxplot(x = power_df['Ia'], orient = 'v', color= 'g', boxprops=dict(alpha=.5))


plt.tight_layout()
plt.show()
```



Seperating fault into healthy categories

No fault

No fault

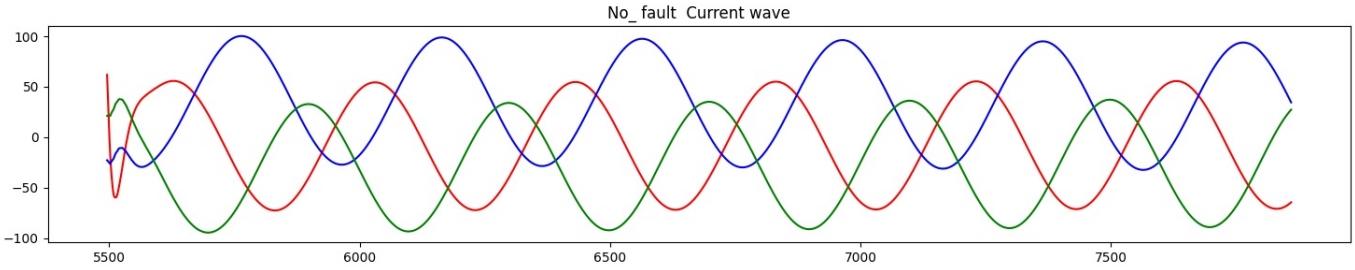
In [ ]:
```
No_fault = power_df[power_df['Fault_Type']=='NO Fault']
No_fault.head()
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
5496	0	0	0	0	61.806321	-22.861987	21.102428	0.366320	-0.567179	0.200859	NO Fault
5497	0	0	0	0	48.041678	-23.401108	21.273066	0.367341	-0.564257	0.196916	NO Fault
5498	0	0	0	0	34.256533	-23.909263	21.408047	0.368258	-0.561168	0.192910	NO Fault
5499	0	0	0	0	20.464350	-24.396165	21.501503	0.369086	-0.557916	0.188830	NO Fault
5500	0	0	0	0	7.109677	-25.075888	21.341967	0.370321	-0.554505	0.184184	NO Fault

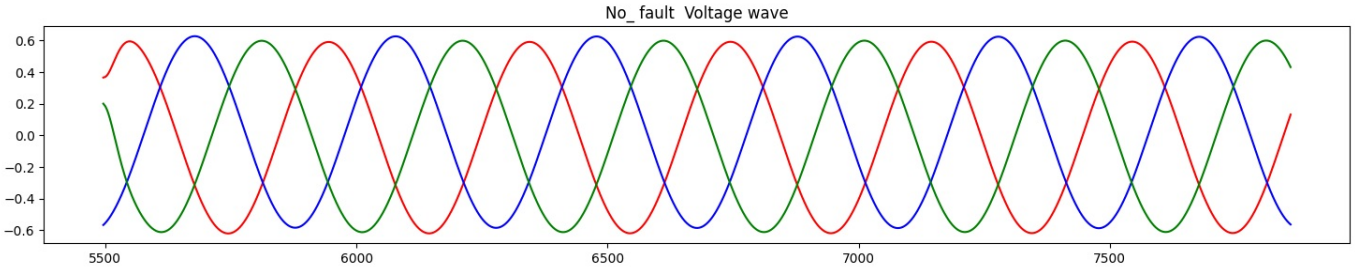
In [ ]:
```
ax = plt.figure(figsize=(18,3))
ax = plt.plot(No_fault['Ia'] , 'r')
ax = plt.plot(No_fault["Ib"],'b')
ax = plt.plot(No_fault["Ic"],'g')
plt.title('No_ fault  Current wave')
```

Out[ ]:
```
Text(0.5, 1.0, 'No_ fault  Current wave')
```



In [ ]:
```
ax = plt.figure(figsize=(18,3))
ax = plt.plot(No_fault['Va'] , 'r')
ax = plt.plot(No_fault["Vb"],'b')
ax = plt.plot(No_fault["Vc"],'g')
plt.title('No_ fault  Voltage wave')
```

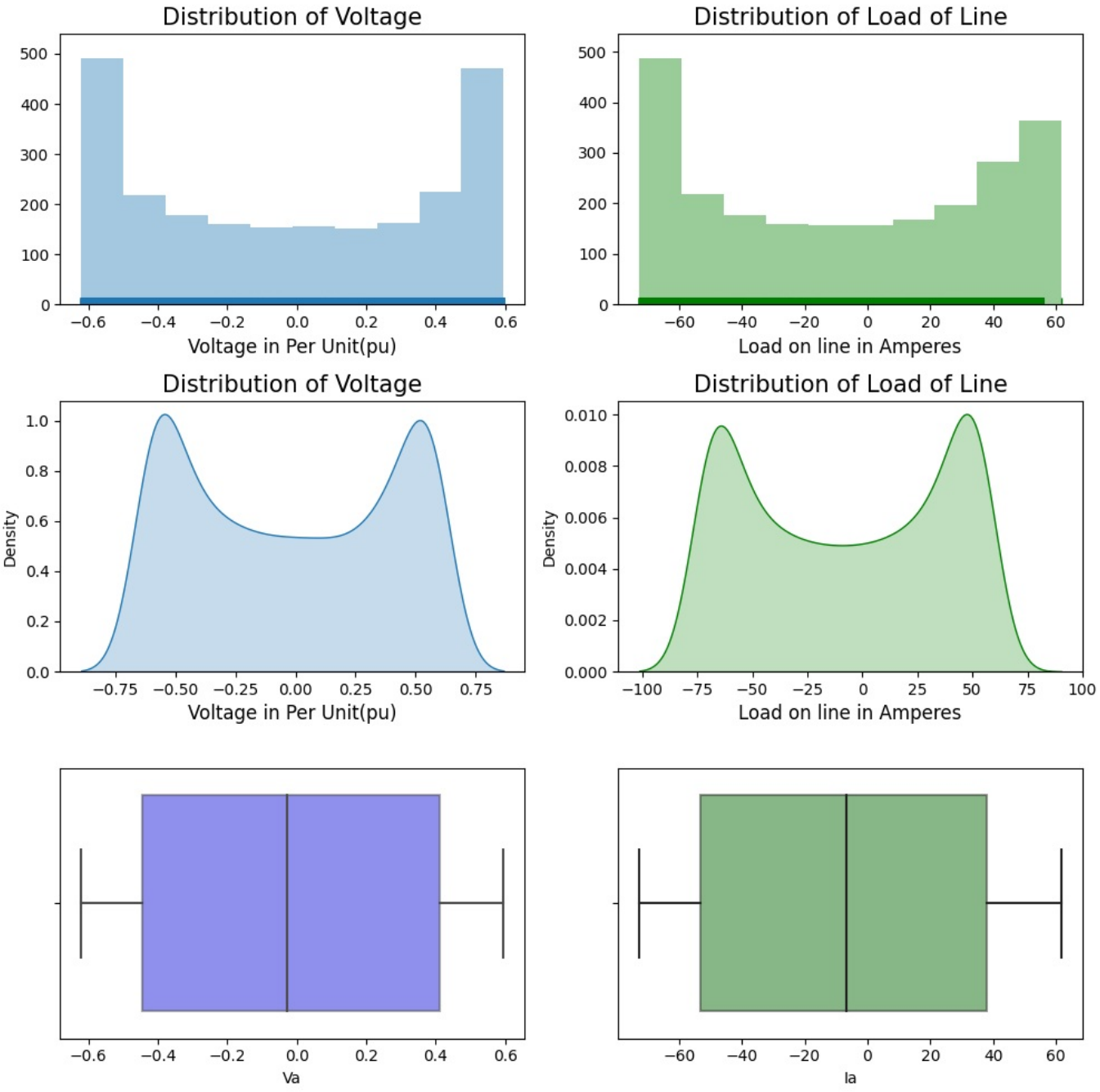
Out[ ]:
```
Text(0.5, 1.0, 'No_ fault  Voltage wave')
```



In a normal (No_Fault) condition Voltage or Current graph, is symmetrical and sinusoidal in nature with current and voltage 120 degree in phase shift and maximum current is approximately +100 to -100 Amperes and voltage +0.5 pu to -0.5pu

In [ ]:
```
plt.figure(figsize= (15,10))
#plt.suptitle("Distributions of Different Features", fontsize = 20)
#Histograms
plt.subplot(3,3,1)
sns.distplot(No_fault['Va'], rug = True, kde = False)
plt.xlabel('Voltage in Per Unit(pu)', fontsize = 12)
plt.title('Distribution of Voltage',fontsize = 15)

plt.subplot(3,3,2)
sns.distplot(No_fault['Ia'], color= 'green',rug = True, kde = False)
plt.title('Distribution of Load of Line',fontsize = 15)
plt.xlabel('Load on line in Amperes', fontsize = 12)


#Kde Plots
plt.subplot(3,3,4)
sns.kdeplot(No_fault['Va'], shade = True)
plt.xlabel('Voltage in Per Unit(pu)', fontsize = 12)
plt.title('Distribution of Voltage',fontsize = 15)

plt.subplot(3,3,5)
sns.kdeplot(No_fault['Ia'], shade = True, color = 'g')
plt.title('Distribution of Load of Line',fontsize = 15)
plt.xlabel('Load on line in Amperes', fontsize = 12)
```

```
#Box Plots
plt.subplot(3,3,7)
sns.boxplot(x = No_fault['Va'], orient = 'v',color= 'b', boxprops=dict(alpha=.5))
plt.subplot(3,3,8)
sns.boxplot(x = No_fault['Ia'], orient = 'v', color= 'g', boxprops=dict(alpha=.5))


plt.tight_layout()
plt.show()
```



Fault sytem with Line A to ground fault

In [ ]:
```
Line_AG_Fault = power_df[power_df['Fault_Type']=='Line A to Ground Fault' ]
Line_AG_Fault.head()
```

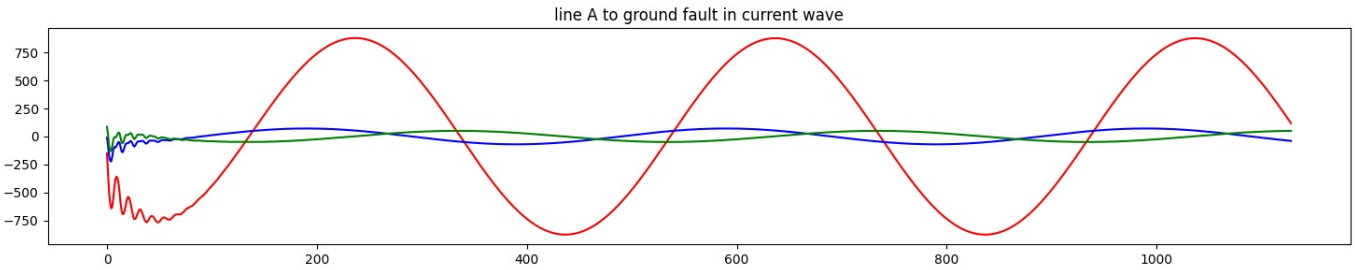
Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
0	1	0	0	1	-151.291812	-9.677452	85.800162	0.400750	-0.132935	-0.267815	Line A to Ground Fault
1	1	0	0	1	-336.186183	-76.283262	18.328897	0.312732	-0.123633	-0.189099	Line A to Ground Fault
2	1	0	0	1	-502.891583	-174.648023	-80.924663	0.265728	-0.114301	-0.151428	Line A to Ground Fault
3	1	0	0	1	-593.941905	-217.703359	-124.891924	0.235511	-0.104940	-0.130570	Line A to Ground Fault
4	1	0	0	1	-643.663617	-224.159427	-132.282815	0.209537	-0.095554	-0.113983	Line A to Ground Fault

In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_AG_Fault["Ia"],'r')
ax = plt.plot(Line_AG_Fault["Ib"],'b')
```

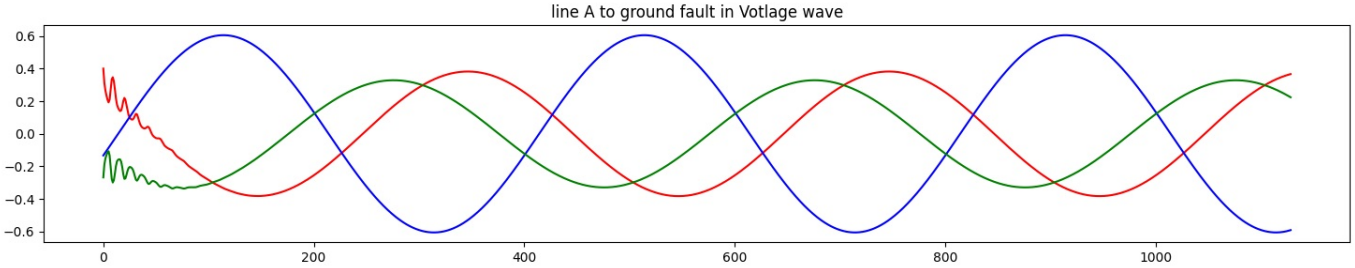
```
ax = plt.plot(Line_AG_Fault["Ic"],'g')
plt.title("line A to ground fault in current wave")
```

Out[ ]:
```
Text(0.5, 1.0, 'line A to ground fault in current wave')
```



In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_AG_Fault["Va"],'r')
ax = plt.plot(Line_AG_Fault["Vb"],'b')
ax = plt.plot(Line_AG_Fault["Vc"],'g')
plt.title("line A to ground fault in Votlage wave")
```

Out[ ]:
```
Text(0.5, 1.0, 'line A to ground fault in Votlage wave')
```



Note: At a time of Line A to grounf fault the current in line A increases to 10 fold approximately 1000 Ampears form normal 100 Ampears and voltage reduced.

Faulty System with Line A ,Line B to Ground Fault

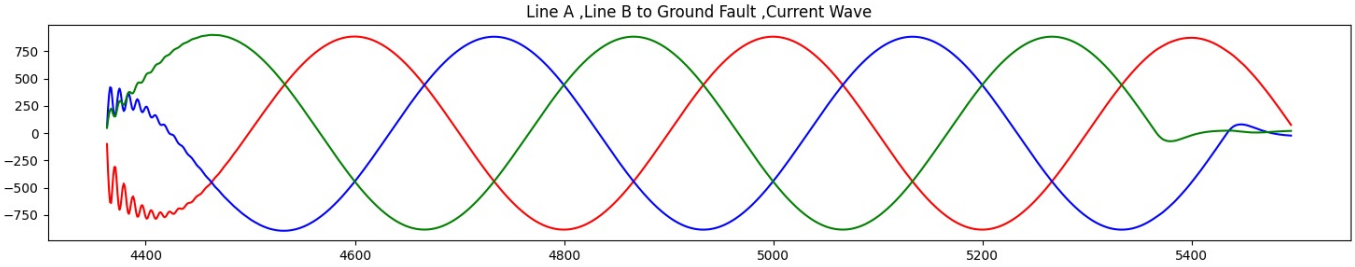
In [ ]:
```
Line_ABG_Fault = power_df[power_df['Fault_Type'] == 'Line A Line B Line C to Ground Fault' ]
Line_ABG_Fault.head(5)
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
4363	1	1	1	1	-99.252463	52.717974	48.341534	0.410059	-0.086914	-0.323145	Line A Line B Line C to Ground Fault
4364	1	1	1	1	-342.238819	224.821345	119.149604	0.095347	-0.002326	-0.093021	Line A Line B Line C to Ground Fault
4365	1	1	1	1	-526.874012	351.614759	176.674369	-0.130437	0.055441	0.074996	Line A Line B Line C to Ground Fault
4366	1	1	1	1	-633.768916	420.246089	214.577137	-0.244709	0.082066	0.162643	Line A Line B Line C to Ground Fault
4367	1	1	1	1	-639.566896	415.329565	225.117414	-0.223359	0.073192	0.150167	Line A Line B Line C to Ground Fault

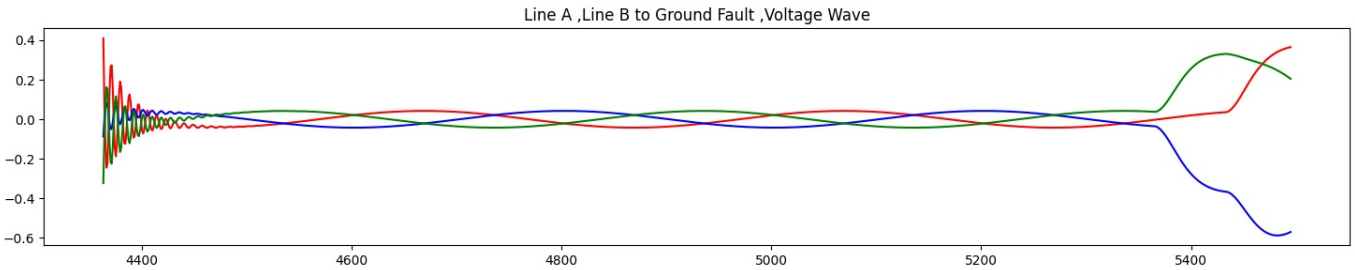
In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_ABG_Fault["Ia"],'r')
ax = plt.plot(Line_ABG_Fault["Ib"],'b')
ax = plt.plot(Line_ABG_Fault["Ic"],'g')
plt.title('Line A ,Line B to Ground Fault ,Current Wave')
```

Out[ ]:
```
Text(0.5, 1.0, 'Line A ,Line B to Ground Fault ,Current Wave')
```



In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_ABG_Fault["Va"],'r')
ax = plt.plot(Line_ABG_Fault["Vb"],'b')
ax = plt.plot(Line_ABG_Fault["Vc"],'g')
plt.title('Line A ,Line B to Ground Fault ,Voltage Wave')
```

Out[ ]:
```
Text(0.5, 1.0, 'Line A ,Line B to Ground Fault ,Voltage Wave')
```



Faulty System with Line B to Line C

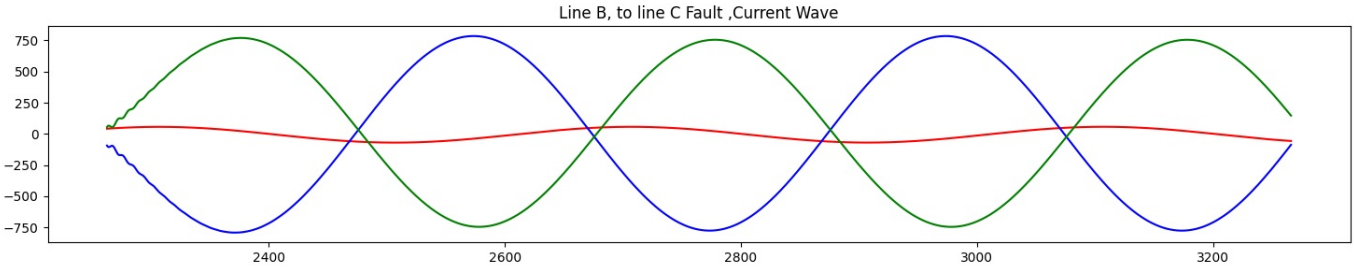
In [ ]:
```
Line_BC_Fault = power_df[power_df['Fault_Type'] == 'Line B to Line C Fault' ]
Line_BC_Fault.head()
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
2263	0	1	1	0	41.764455	-93.940215	55.022192	0.517510	-0.003685	-0.513825	Line B to Line C Fault
2264	0	1	1	0	42.394348	-105.038998	65.494029	0.518491	-0.008071	-0.510420	Line B to Line C Fault
2265	0	1	1	0	43.010571	-105.734383	65.569977	0.511217	0.003798	-0.515015	Line B to Line C Fault
2266	0	1	1	0	43.612456	-100.121739	59.347319	0.499096	0.025105	-0.524201	Line B to Line C Fault
2267	0	1	1	0	44.202230	-95.078643	53.707382	0.487527	0.045052	-0.532579	Line B to Line C Fault

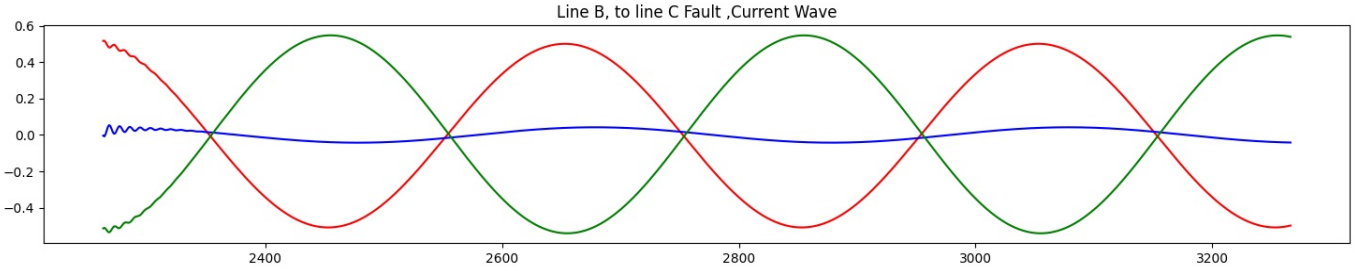
In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_BC_Fault["Ia"],'r')
ax = plt.plot(Line_BC_Fault["Ib"],'b')
ax = plt.plot(Line_BC_Fault["Ic"],'g')
plt.title('Line B, to line C Fault ,Current Wave')
```

Out[ ]:
```
Text(0.5, 1.0, 'Line B, to line C Fault ,Current Wave')
```



In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_BC_Fault["Va"],'r')
ax = plt.plot(Line_BC_Fault["Vb"],'b')
ax = plt.plot(Line_BC_Fault["Vc"],'g')
plt.title('Line B, to line C Fault ,Current Wave')
```

Out[ ]:
```
Text(0.5, 1.0, 'Line B, to line C Fault ,Current Wave')
```



Faulty System with Line A - Line B - Line C

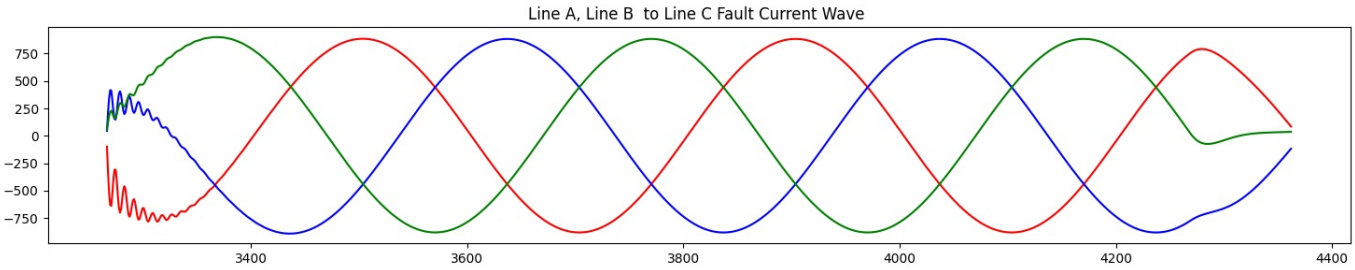
In [ ]:
```
Line_ABC_Fault = power_df[power_df['Fault_Type'] == 'Line A  Line B  Line C Fault' ]
Line_ABC_Fault.head(5)
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
3267	0	1	1	1	-99.274309	44.146905	57.318650	0.412305	-0.091525	-0.320781	Line A Line B Line C Fault
3268	0	1	1	1	-342.196277	218.566556	125.820753	0.095905	-0.003471	-0.092434	Line A Line B Line C Fault
3269	0	1	1	1	-526.696029	347.197345	181.689494	-0.131094	0.056790	0.074304	Line A Line B Line C Fault
3270	0	1	1	1	-633.453623	416.942091	218.702118	-0.245984	0.084683	0.161301	Line A Line B Line C Fault
3271	0	1	1	1	-639.192926	412.122656	229.260639	-0.224523	0.075580	0.148943	Line A Line B Line C Fault

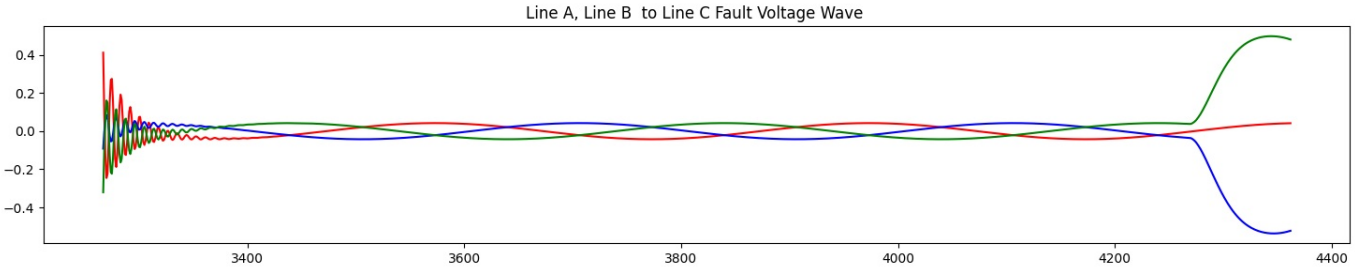
In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_ABC_Fault["Ia"],'r')
ax = plt.plot(Line_ABC_Fault["Ib"],'b')
ax = plt.plot(Line_ABC_Fault["Ic"],'g')
plt.title('Line A, Line B  to Line C Fault Current Wave ')
```

Out[ ]:
```
Text(0.5, 1.0, 'Line A, Line B  to Line C Fault Current Wave ')
```



In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_ABC_Fault["Va"],'r')
ax = plt.plot(Line_ABC_Fault["Vb"],'b')
ax = plt.plot(Line_ABC_Fault["Vc"],'g')
plt.title('Line A, Line B  to Line C Fault Voltage Wave ')
```

Out[ ]:
```
Text(0.5, 1.0, 'Line A, Line B  to Line C Fault Voltage Wave ')
```



Faulty System with Line A - Line B - Line C - Ground

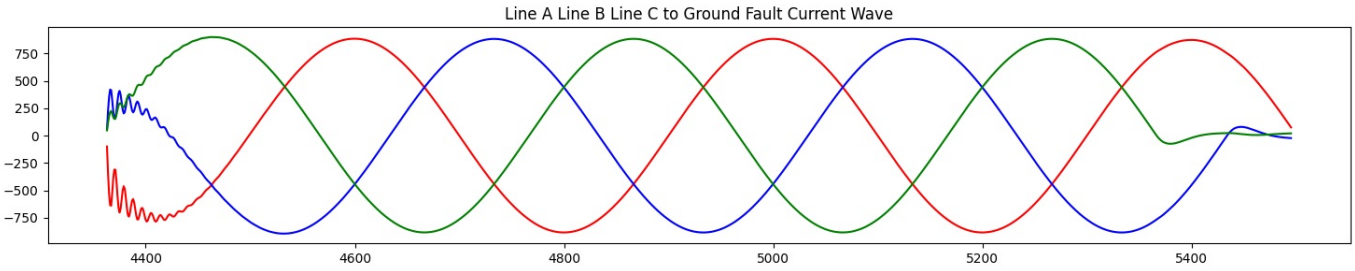
In [ ]:
```
Line_ABCG_Fault = power_df[power_df['Fault_Type'] == 'Line A Line B Line C to Ground Fault']
Line_ABCG_Fault.head()
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
4363	1	1	1	1	-99.252463	52.717974	48.341534	0.410059	-0.086914	-0.323145	Line A Line B Line C to Ground Fault
4364	1	1	1	1	-342.238819	224.821345	119.149604	0.095347	-0.002326	-0.093021	Line A Line B Line C to Ground Fault
4365	1	1	1	1	-526.874012	351.614759	176.674369	-0.130437	0.055441	0.074996	Line A Line B Line C to Ground Fault
4366	1	1	1	1	-633.768916	420.246089	214.577137	-0.244709	0.082066	0.162643	Line A Line B Line C to Ground Fault
4367	1	1	1	1	-639.566896	415.329565	225.117414	-0.223359	0.073192	0.150167	Line A Line B Line C to Ground Fault

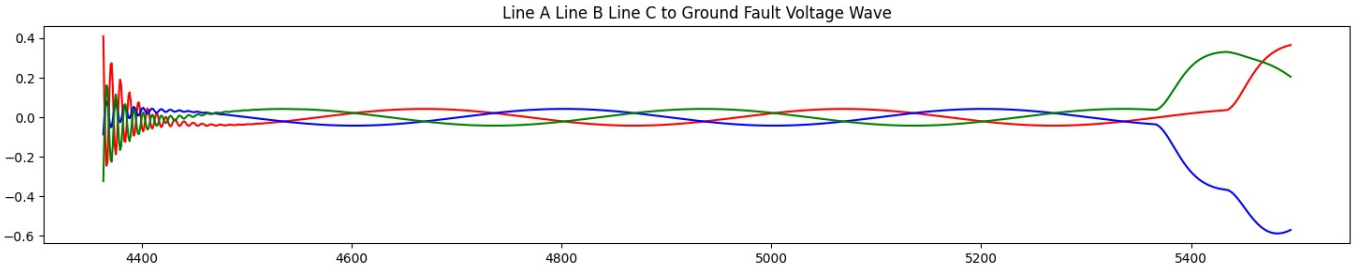
In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_ABCG_Fault["Ia"],'r')
ax = plt.plot(Line_ABCG_Fault["Ib"],'b')
ax = plt.plot(Line_ABCG_Fault["Ic"],'g')
plt.title("Line A Line B Line C to Ground Fault Current Wave")
```

Out[ ]:
```
Text(0.5, 1.0, 'Line A Line B Line C to Ground Fault Current Wave')
```



In [ ]:
```
ax = plt.figure(figsize = (18,3))
ax = plt.plot(Line_ABCG_Fault["Va"],'r')
ax = plt.plot(Line_ABCG_Fault["Vb"],'b')
ax = plt.plot(Line_ABCG_Fault["Vc"],'g')
plt.title("Line A Line B Line C to Ground Fault Voltage Wave")
```

Out[ ]:
```
Text(0.5, 1.0, 'Line A Line B Line C to Ground Fault Voltage Wave')
```



In [ ]:
```
print(power_df['Fault_Type'].unique())
```

```
['Line A to Ground Fault' 'Line A Line B to GroundFault'
 'Line B to Line C Fault' 'Line A  Line B  Line C Fault'
 'Line A Line B Line C to Ground Fault' 'NO Fault']
```

Categorical to Numerical conversion

In [ ]:
```
from  sklearn.preprocessing import LabelEncoder
encoder =LabelEncoder()
power_df['Fault_Type'] = encoder.fit_transform(power_df['Fault_Type'])

power_df.head()
```

Out[ ]:

	G	C	B	A	Ia	Ib	Ic	Va	Vb	Vc	Fault_Type
0	1	0	0	1	-151.291812	-9.677452	85.800162	0.400750	-0.132935	-0.267815	3
1	1	0	0	1	-336.186183	-76.283262	18.328897	0.312732	-0.123633	-0.189099	3
2	1	0	0	1	-502.891583	-174.648023	-80.924663	0.265728	-0.114301	-0.151428	3
3	1	0	0	1	-593.941905	-217.703359	-124.891924	0.235511	-0.104940	-0.130570	3
4	1	0	0	1	-643.663617	-224.159427	-132.282815	0.209537	-0.095554	-0.113983	3

Features and Target sepration

In [ ]:
```
power_df['Fault_Type'] = power_df['Fault_Type'].values.reshape(-1)
X = power_df.drop(['Fault_Type'], axis =1)
y = power_df['Fault_Type']
print(X.shape[1])
print(y.shape[0])
```

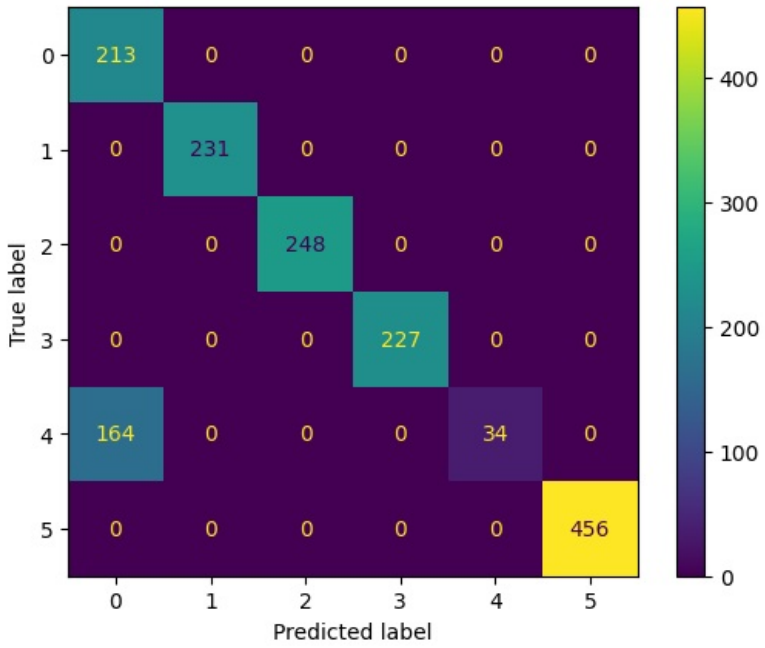
```
10
7861
```

In [ ]:
```
from sklearn.model_selection import train_test_split
X_train ,X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,
                                                    random_state =21)
```

logistic regression

In [ ]:
```
from sklearn.metrics import accuracy_score ,classification_report,confusion_matrix,ConfusionMatrixDisplay

# Logistic regression
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(X_train,y_train)
y_pred_lr = logreg.predict(X_test)

log_train = round(logreg.score(X_train ,y_train)*100 ,2)
log_accuracy = round(accuracy_score(y_pred_lr ,y_test)*100 ,2)

print("Training Accuracy    :",log_train ,"%")
print("Model Accuracy Score :",log_accuracy ,"%")
print("----------------------------------------------------------")
print("Classification_Report: \n",classification_report(y_test,y_pred_lr))
print("----------------------------------------------------------")

cm = confusion_matrix(y_test, y_pred_lr, labels=logreg.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=logreg.classes_)
disp.plot()
plt.show()
```

```
Training Accuracy    : 90.11 %
Model Accuracy Score : 89.57 %
----------------------------------------------------------
Classification_Report:
               precision    recall  f1-score   support

           0       0.56      1.00      0.72       213
           1       1.00      1.00      1.00       231
           2       1.00      1.00      1.00       248
           3       1.00      1.00      1.00       227
           4       1.00      0.17      0.29       198
           5       1.00      1.00      1.00       456

    accuracy                           0.90      1573
   macro avg       0.93      0.86      0.84      1573
weighted avg       0.94      0.90      0.87      1573

----------------------------------------------------------
```

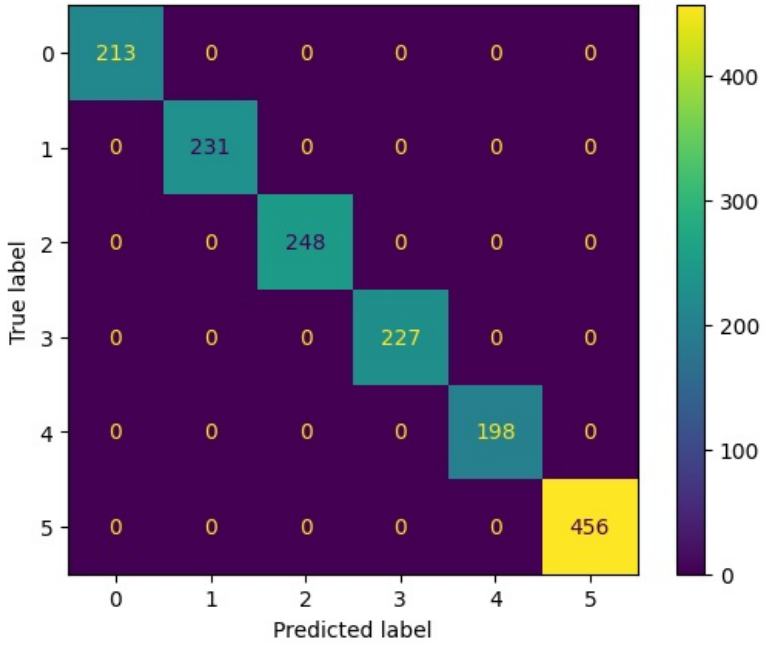


Decision Tree Classifier

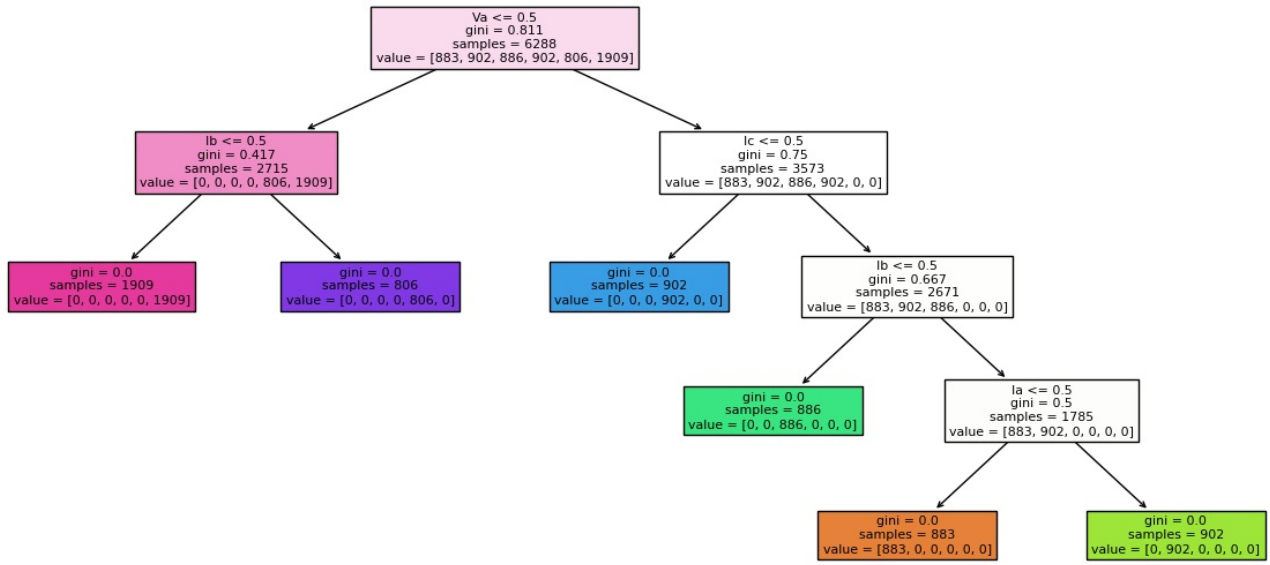
In [ ]:
```
# Decision Tree
from sklearn.tree import DecisionTreeClassifier
decision =DecisionTreeClassifier()
decision.fit(X_train ,y_train)
y_pred_dec = decision.predict(X_test)

decision_train = round(decision.score(X_train, y_train) * 100, 2)
decision_accuracy = round(accuracy_score(y_pred_dec, y_test) * 100, 2)

print("Training Accuracy    :",decision_train ,"%")
print("Model Accuracy Score :",decision_accuracy ,"%")
print("----------------------------------------------------------")
```

```
print("Classification_Report: \n",classification_report(y_test,y_pred_dec))
print("------------------------------------------------------------")

dt_cm = confusion_matrix(y_test, y_pred_dec, labels=decision.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=dt_cm,
                              display_labels=decision.classes_)
disp.plot()
plt.show()
```

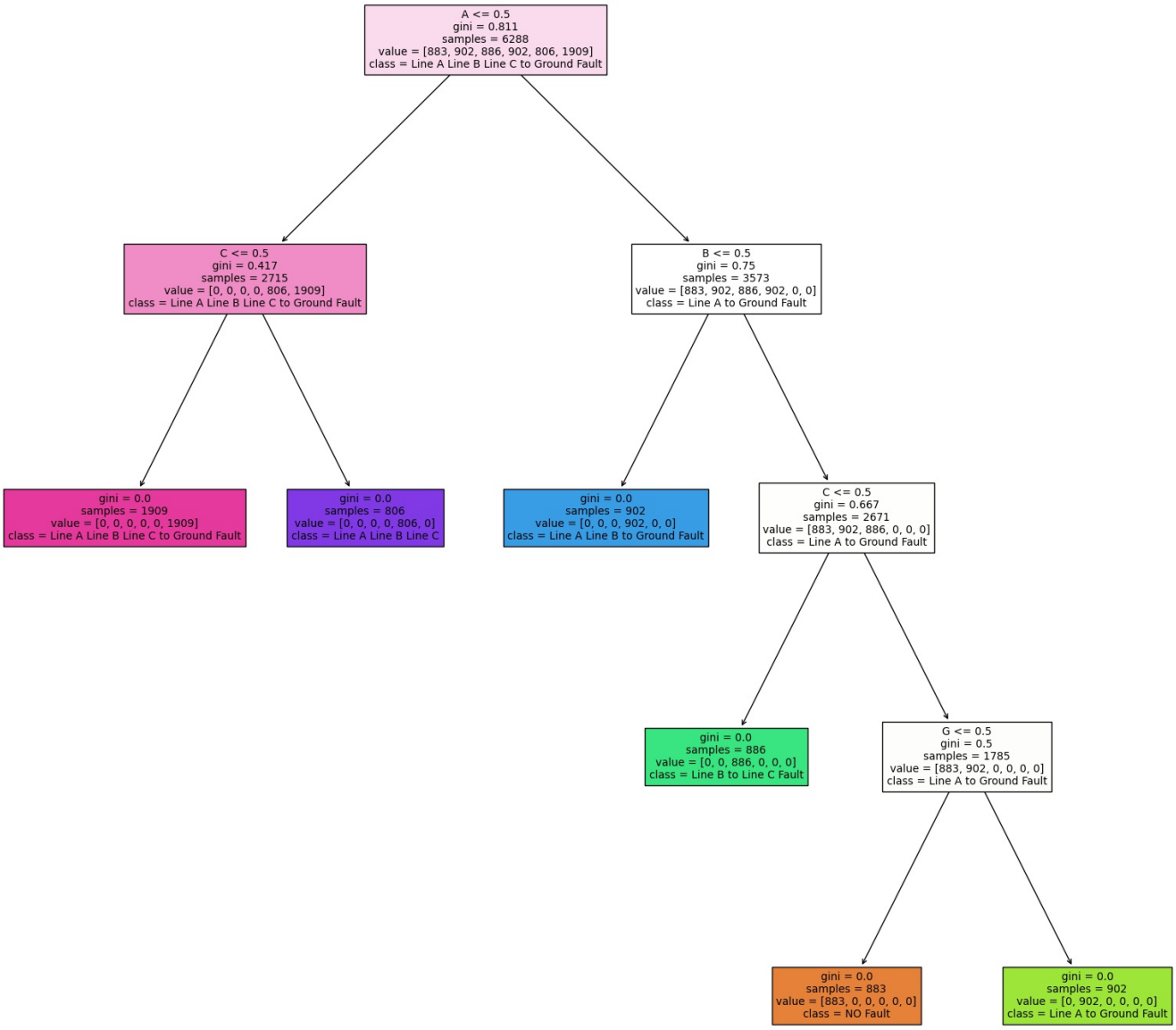
```
Training Accuracy    : 100.0 %
Model Accuracy Score : 100.0 %
------------------------------------------------------------
Classification_Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       213
           1       1.00      1.00      1.00       231
           2       1.00      1.00      1.00       248
           3       1.00      1.00      1.00       227
           4       1.00      1.00      1.00       198
           5       1.00      1.00      1.00       456

    accuracy                           1.00      1573
   macro avg       1.00      1.00      1.00      1573
weighted avg       1.00      1.00      1.00      1573

------------------------------------------------------------
```



In [ ]:
```
from sklearn.tree import plot_tree
plt.figure(figsize=(15,7))
plot_tree(decision,filled=True,feature_names=['Ia', 'Ib', 'Ic', 'Va', 'Vb', 'Vc'])
plt.show()
```



In [ ]:
```
from sklearn import tree
def tree_plot(model_name):
    plt.figure(figsize=(20,20))
    features = power_df.columns
    classes = ['NO Fault','Line A to Ground Fault','Line B to Line C Fault','Line A Line B to Ground Fault','Li
    tree.plot_tree(model_name,feature_names=features,class_names=classes,filled=True)
    plt.show()
tree_plot(decision)
```

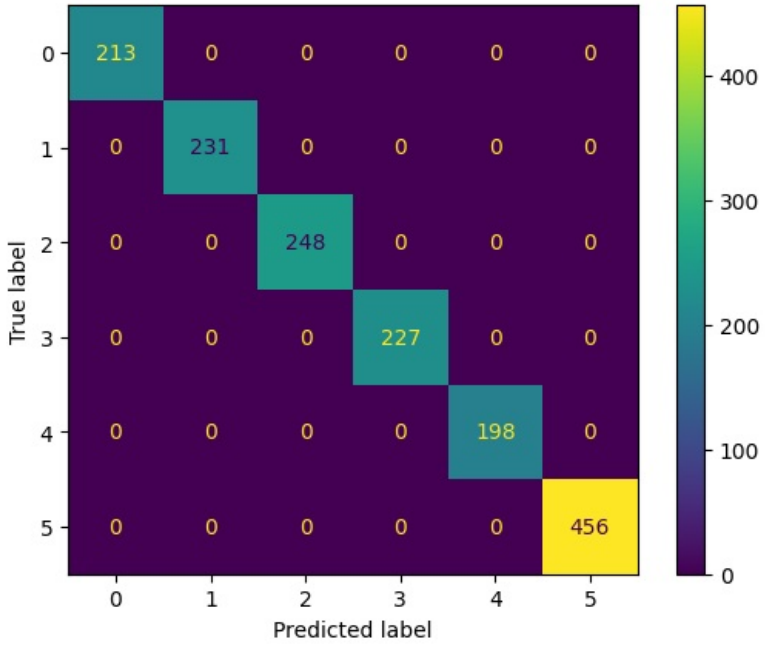


Random Forest Classifier

In [ ]:
```
# Decision Tree
from sklearn.ensemble import RandomForestClassifier
randome_forest =RandomForestClassifier()
randome_forest.fit(X_train ,y_train)
y_pred_rf = randome_forest.predict(X_test)

rf_train = round(decision.score(X_train, y_train) * 100, 2)
rf_accuracy = round(accuracy_score(y_pred_rf, y_test) * 100, 2)

print("Training Accuracy    :",rf_train ,"%")
print("Model Accuracy Score :",rf_accuracy ,"%")
print("----------------------------------------------------------")
print("Classification_Report: \n",classification_report(y_test,y_pred_rf))
print("----------------------------------------------------------")

dt_cm = confusion_matrix(y_test, y_pred_rf, labels=randome_forest.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=dt_cm,
                              display_labels=randome_forest.classes_)
disp.plot()
```

```
plt.show()
```

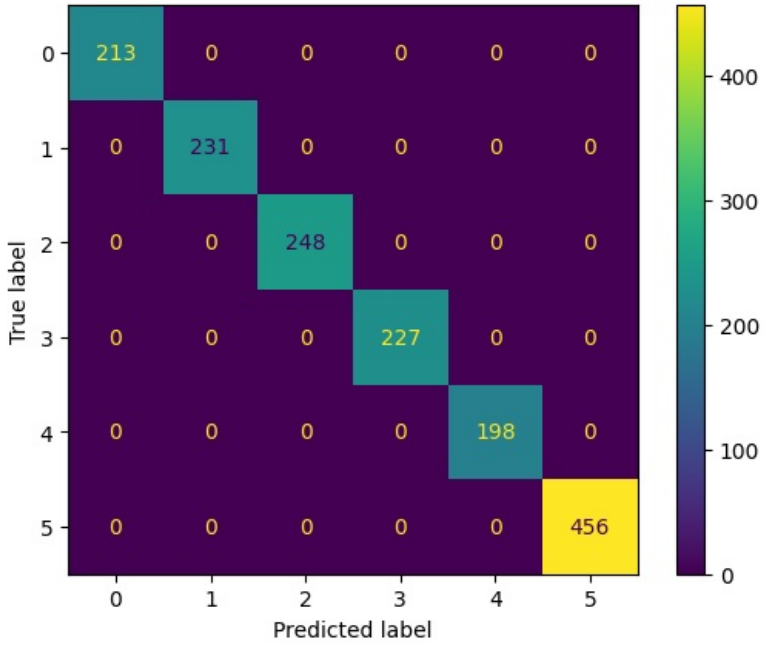
```
Training Accuracy    : 100.0 %
Model Accuracy Score : 100.0 %
-----------------------------------------------------------
Classification_Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       213
           1       1.00      1.00      1.00       231
           2       1.00      1.00      1.00       248
           3       1.00      1.00      1.00       227
           4       1.00      1.00      1.00       198
           5       1.00      1.00      1.00       456

    accuracy                           1.00      1573
   macro avg       1.00      1.00      1.00      1573
weighted avg       1.00      1.00      1.00      1573

-----------------------------------------------------------
```



XGB Classifier

In [ ]:
```
import xgboost as Xgb
xgb = Xgb.XGBClassifier()
xgb.fit(X_train,y_train)
y_pred_xgb = xgb.predict(X_test)
xgb.score(X_train, y_train)

xgb_train = round(decision.score(X_train, y_train) * 100, 2)
xgb_accuracy = round(accuracy_score(y_pred_xgb, y_test) * 100, 2)

print("Training Accuracy    :",xgb_train ,"%")
print("Model Accuracy Score :",xgb_accuracy ,"%")
print("-----------------------------------------------------------")
print("Classification_Report: \n",classification_report(y_test,y_pred_xgb))
print("-----------------------------------------------------------")

xgb_cm = confusion_matrix(y_test, y_pred_xgb, labels=xgb.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=xgb_cm,
                              display_labels=xgb.classes_)
disp.plot()
plt.show()
```

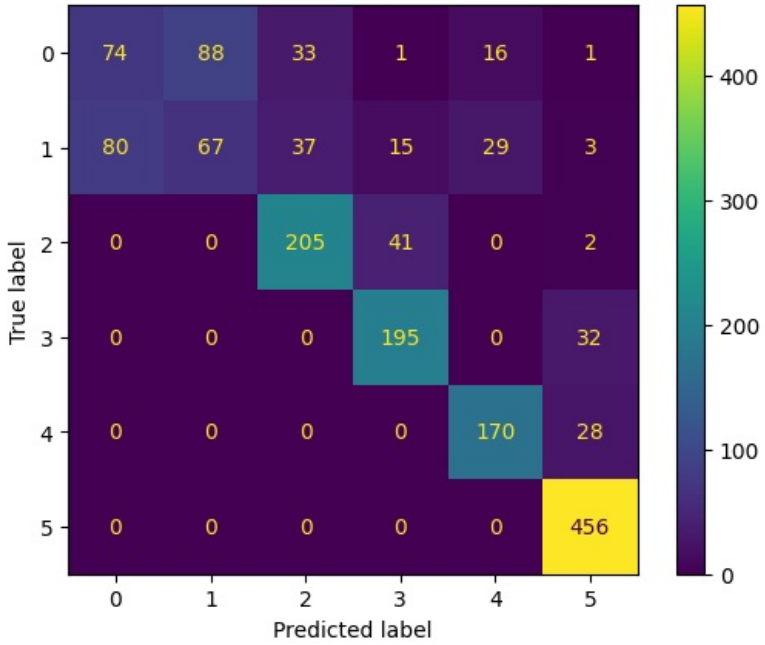
```
Training Accuracy    : 100.0 %
Model Accuracy Score : 100.0 %
------------------------------------------------------
Classification_Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       213
           1       1.00      1.00      1.00       231
           2       1.00      1.00      1.00       248
           3       1.00      1.00      1.00       227
           4       1.00      1.00      1.00       198
           5       1.00      1.00      1.00       456

    accuracy                           1.00      1573
   macro avg       1.00      1.00      1.00      1573
weighted avg       1.00      1.00      1.00      1573

------------------------------------------------------
```



SVM (support vector machines)

In [ ]:
```
from sklearn.svm import SVC
svc = SVC()
svc.fit(X_train,y_train)
y_pred_svc = svc.predict(X_test)
svc.score(X_train, y_train)

svc_train = round(decision.score(X_train, y_train) * 100, 2)
svc_accuracy = round(accuracy_score(y_pred_xgb, y_test) * 100, 2)

print("Training Accuracy    :",svc_train ,"%")
print("Model Accuracy Score :",svc_accuracy ,"%")
print("------------------------------------------------------")
print("Classification_Report: \n",classification_report(y_test,y_pred_svc))
print("------------------------------------------------------")

svc_cm = confusion_matrix(y_test, y_pred_svc, labels=svc.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=svc_cm,
                              display_labels=svc.classes_)
disp.plot()
plt.show()
```

```
Training Accuracy    : 100.0 %
Model Accuracy Score : 100.0 %
--------------------------------------------------------
Classification_Report:
              precision    recall  f1-score   support

           0       0.48      0.35      0.40       213
           1       0.43      0.29      0.35       231
           2       0.75      0.83      0.78       248
           3       0.77      0.86      0.81       227
           4       0.79      0.86      0.82       198
           5       0.87      1.00      0.93       456

    accuracy                           0.74      1573
   macro avg       0.68      0.70      0.68      1573
weighted avg       0.71      0.74      0.72      1573

--------------------------------------------------------
```



-------Comparing Different Models----------

In [ ]:
```
models = pd.DataFrame({
    'Model': [
        'Support Vector Machines', 'Logistic Regression', 'Random Forest',
        'Decision Tree', 'XGBClassifier'
    ],

    'Training Accuracy':
    [log_train, svc_train, decision_train, rf_train, xgb_train],

    'Model Accuracy Score': [
        log_accuracy, svc_accuracy, decision_accuracy, rf_accuracy,
        xgb_accuracy
    ]
})
```

In [ ]:
```
pd.set_option("display.max_columns", 100)
models.sort_values(by='Model Accuracy Score', ascending=False)
```

Out[ ]:

	Model	Training Accuracy	Model Accuracy Score
1	Logistic Regression	100.00	100.00
2	Random Forest	100.00	100.00
3	Decision Tree	100.00	100.00
4	XGBClassifier	100.00	100.00
0	Support Vector Machines	90.11	89.57

Result prediction

In [ ]:
```
print("Random Forest Classifier")
prediction1 = randome_forest.predict(X_test)
print(prediction1)
cross_checking = pd.DataFrame({'Actual' : y_test , 'Predicted' : prediction1})
```

```
print(cross_checking.head(5))



print('====================================================================')

print("logistic regression")
prediction2 = logreg.predict(X_test)
print(prediction2)
cross_checking2 = pd.DataFrame({'Actual' : y_test , 'Predicted' : prediction2})
print(cross_checking2.head(5))


print('====================================================================')

print("Decision tree")
prediction3 = decision.predict(X_test)
print(prediction3)
cross_checking3 = pd.DataFrame({'Actual' : y_test , 'Predicted' : prediction3})
print(cross_checking3.head(5))


print('====================================================================')

print("XGB Classifier")
prediction4 = xgb.predict(X_test)
print(prediction4)
cross_checking4 = pd.DataFrame({'Actual' : y_test , 'Predicted' : prediction4})
print(cross_checking4.head(5))

print('====================================================================')

print("SVC Classifier")
prediction5 = svc.predict(X_test)
print(prediction5)
cross_checking5 = pd.DataFrame({'Actual' : y_test , 'Predicted' : prediction5})
print(cross_checking5.head(5))

print('====================================================================')
```

```
Random Forest Classifier
[1 0 0 ... 0 0 5]
      Actual  Predicted
4530       1          1
3669       0          0
3902       0          0
6000       5          5
5053       1          1
================================================================
logistic regression
[1 0 0 ... 0 0 5]
      Actual  Predicted
4530       1          1
3669       0          0
3902       0          0
6000       5          5
5053       1          1
================================================================
Decision tree
[1 0 0 ... 0 0 5]
      Actual  Predicted
4530       1          1
3669       0          0
3902       0          0
6000       5          5
5053       1          1
================================================================
XGB Classifier
[1 0 0 ... 0 0 5]
      Actual  Predicted
4530       1          1
3669       0          0
3902       0          0
6000       5          5
5053       1          1
================================================================
SVC Classifier
[0 2 1 ... 0 2 5]
      Actual  Predicted
4530       1          0
3669       0          2
3902       0          1
6000       5          5
5053       1          0
================================================================
```