Titanic decision tree algorithm

Project Report
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DEVI AHILYA VISHWAVIDHYALYA INDORE

In Partial Fulfillment of the Requirements
for the Degree of

MASTER OF TECHNOLOGY

in

BIG DATA ANALYTIC

by

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Under the Supervision of

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SCHOOL OF DATA SCIENCE AND FORECASTING

2022-23

DECLARATION

I hereby declare that the work presented in this project report entitled “Titanic decision tree algorithm” was carried out by me. I have not submitted the matter embodied in this report for the award of any other degree or diploma of any other University or Institute. I have given due credit to the original authors/sources for all the words, ideas, diagrams, graphics, computer programs, experiments, results, that are not my original contribution. I have used quotation marks to identify verbatim sentences and given credit to the original authors/sources. I affirm that no portion of my work is plagiarized, and the experiments and results reported in the project report are not manipulated. In the event of a complaint of plagiarism and the manipulation of the experiments and results, I shall be fully responsible and answerable.

Manish Kumar Singh

DS7B-2206

(Candidate Signature)

CERTIFICATE

Certified that Manish Kumar Singh (roll number DS7B-2206) has carried out the project work titled "Titanic decision tree algorithm" for the award of Master of Technology in Big Data Analytic DEVI AHILYA VISHWAVIDHYALYA INDORE under my supervision. The work embodies results of work, carried out by the student himself/herself and the contents of the work do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

Name of Supervisor: Dr. Dinesh Bhati

Designation: Assistant Professor

Signature

Date

Head of the Department: Dr. V.B Gupta

Signature

Date

ABSTRACT

The sinking of the Titanic is one of the most infamous shipwrecks in history.
On April 15, 1912, during her maiden voyage, the widely considered “unsinkable” RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren’t enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew.
While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.
In this challenge, we ask you to build a predictive model that answers the question: “what sorts of people were more likely to survive?” using passenger data (ie name, age, gender, socio-economic class, etc).

kaggle - Titanic Problem

importing pandas and numpy libraries
pandas - data manipulation
numpy for numerical calculations

In [1]:
```
import pandas as pd
```

In [2]:
```
import numpy as np
```

Loading the datasets

In [4]:
```
data_train = pd.read_csv('train.csv')
```

In [5]:
```
data_test = pd.read_csv('test.csv')
```

In [6]:
```
data_train.columns
```

Out[6]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

Checking whether the data is Balanced/Imbalanced

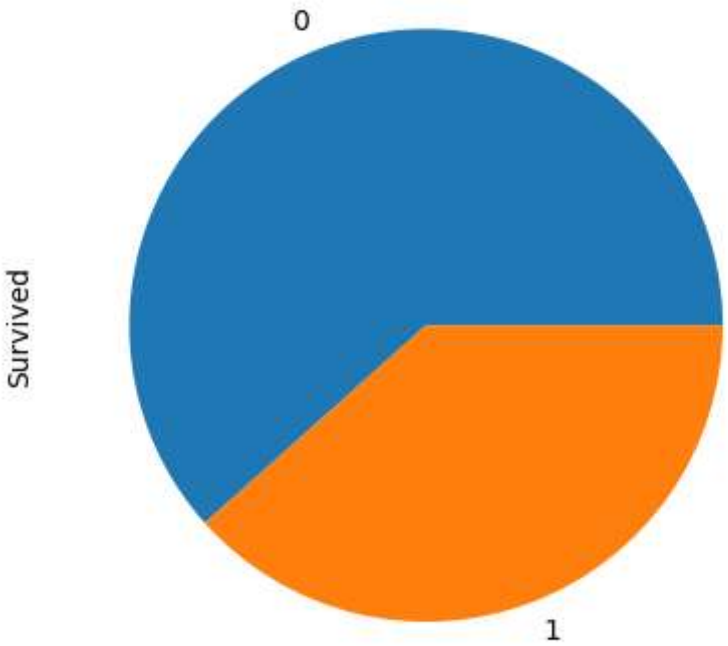
In [7]:
```
import matplotlib.pyplot as plt
```

In [8]:
```
data_train.Survived.value_counts()
```

Out[8]:
```
0    549
1    342
Name: Survived, dtype: int64
```

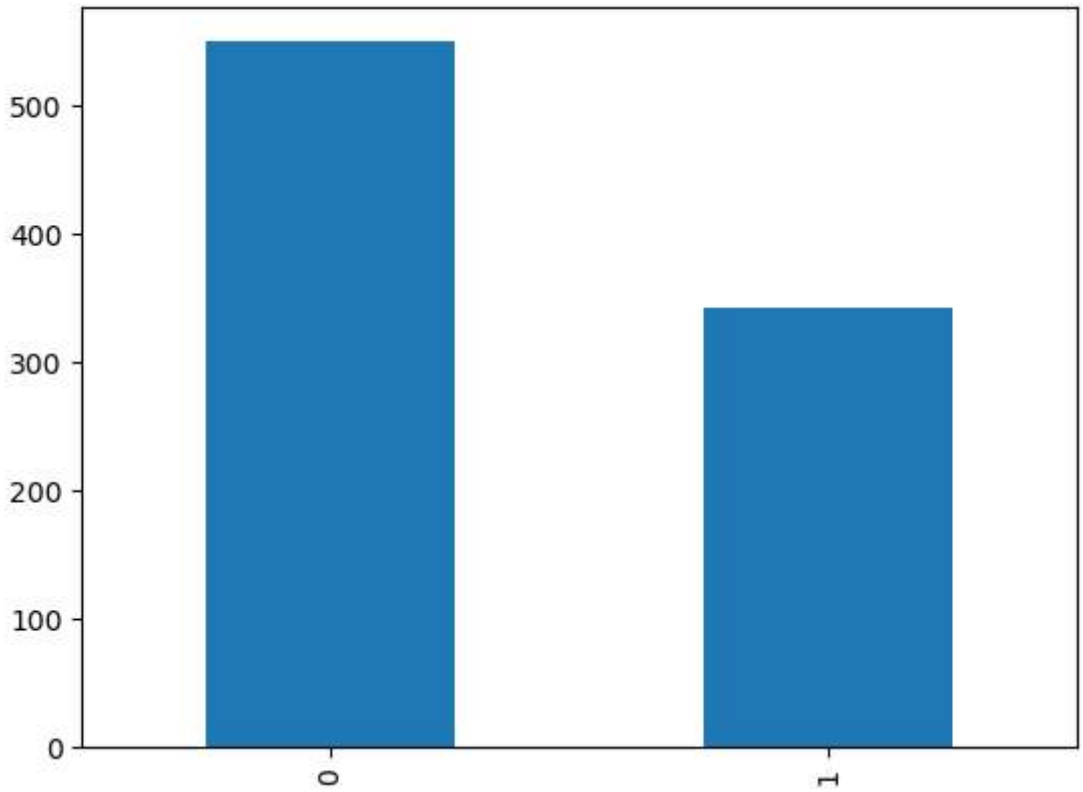
In [9]:
```
data_train.Survived.value_counts().plot.pie() # pie chart
```

Out[9]: <AxesSubplot:ylabel='Survived'>



In [10]:
```
data_train.Survived.value_counts().plot.bar() # barplot - # Imbalanced Dataset
```

Out[10]: <AxesSubplot:>



moving the output variable to index 0 position

In [11]:
```
data_train = data_train.iloc[:, [1,0,2,3,4,5,6,7,8,9,10,11]]
```

In [12]:
```
data_train.head()
```

Out[12]:

	Survived	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	0	1	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	1	2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	1	3	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
3	1	4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C12
4	0	5	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na

In [13]:
```
data_train.columns
```

Out[13]:
```
Index(['Survived', 'PassengerId', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

Categorical Features in Dataset

In [14]:
```
data_train.Survived.value_counts() # 0- Not Survived, 1 - Survived - Ordinal
```

Out[14]:
```
0    549
1    342
Name: Survived, dtype: int64
```

In [15]:
```
data_train.Pclass.value_counts() # 1 - 1st class, 2 - 2nd class, 3 - 3rd class -
```

Out[15]:
```
3    491
1    216
2    184
Name: Pclass, dtype: int64
```

In [16]:
```
data_train.Sex.value_counts() # male, female - Nominal data
```

Out[16]:
```
male      577
female    314
Name: Sex, dtype: int64
```

In [17]:
```
data_train.Embarked.value_counts()
```

Out[17]:
```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [18]:
```
des = data_train.describe()
```

dropping the Irrelavent Features on training dataset

In [19]:
```
data_train_mod = data_train.drop('Name', axis = 1)
```

In [20]:
```
data_train_mod = data_train_mod.drop('Ticket', axis = 1)
```

In [21]:
```
data_train_mod = data_train_mod.drop('Cabin', axis = 1)
```

dropping the Irrelavent Features on test dataset

In [22]:
```
data_test_mod = data_test.drop('Name', axis = 1)
```

In [23]:
```
data_test_mod = data_test_mod.drop('Ticket', axis = 1)
```

In [24]:
```
data_test_mod = data_test_mod.drop('Cabin', axis = 1)
```

EDA - Exploratory Data Analysis - Feature Wise
1 - Survived - Categorical Feature
So Mean, Median is not required
1st moment of business decision

In [25]:
```
data_train_mod['Survived'].mode()
```

Out[25]:
```
0    0
Name: Survived, dtype: int64
```

2 - Pclass - Categorical Feature

In [26]:
```
data_train_mod['Pclass'].mode()
```

Out[26]:
```
0    3
Name: Pclass, dtype: int64
```

In [27]:
```
data_train_mod['Pclass'].min()
```

Out[27]:
```
1
```

In [28]:
```
data_train_mod['Pclass'].max()
```

Out[28]:
```
3
```

In [29]:
```
data_train_mod['Pclass'].max() - data_train_mod['Pclass'].min()
```

Out[29]:
```
2
```

3 - Sex - Categorical Feature

In [30]:
```
data_train_mod['Sex'].mode()  # need to convert it into Numerical in Data preproc
```

Out[30]:
```
0    male
Name: Sex, dtype: object
```

4 - Age - Numerical Feature

In [31]:
```
data_train_mod['Age'].mean()
```

Out[31]:
```
29.69911764705882
```

In [32]:
```
data_train_mod['Age'].median()
```

Out[32]:
```
28.0
```

In [33]:
```
data_train_mod['Age'].mode()
```

Out[33]:
```
0    24.0
Name: Age, dtype: float64
```

In [34]:
```
data_train_mod['Age'].var()
```

Out[34]:
```
211.0191247463081
```

In [35]:
```
data_train_mod['Age'].std()
```

Out[35]:
```
14.526497332334044
```

In [36]:
```
data_train_mod['Age'].min()
```

Out[36]:
```
0.42
```

In [37]:
```
data_train_mod['Age'].max()
```

Out[37]:
```
80.0
```

In [38]:
```
data_train_mod['Age'].max() - data_train_mod['Age'].min()
```

Out[38]:
```
79.58
```

In [39]:
```
data_train_mod['Age'].skew()
```

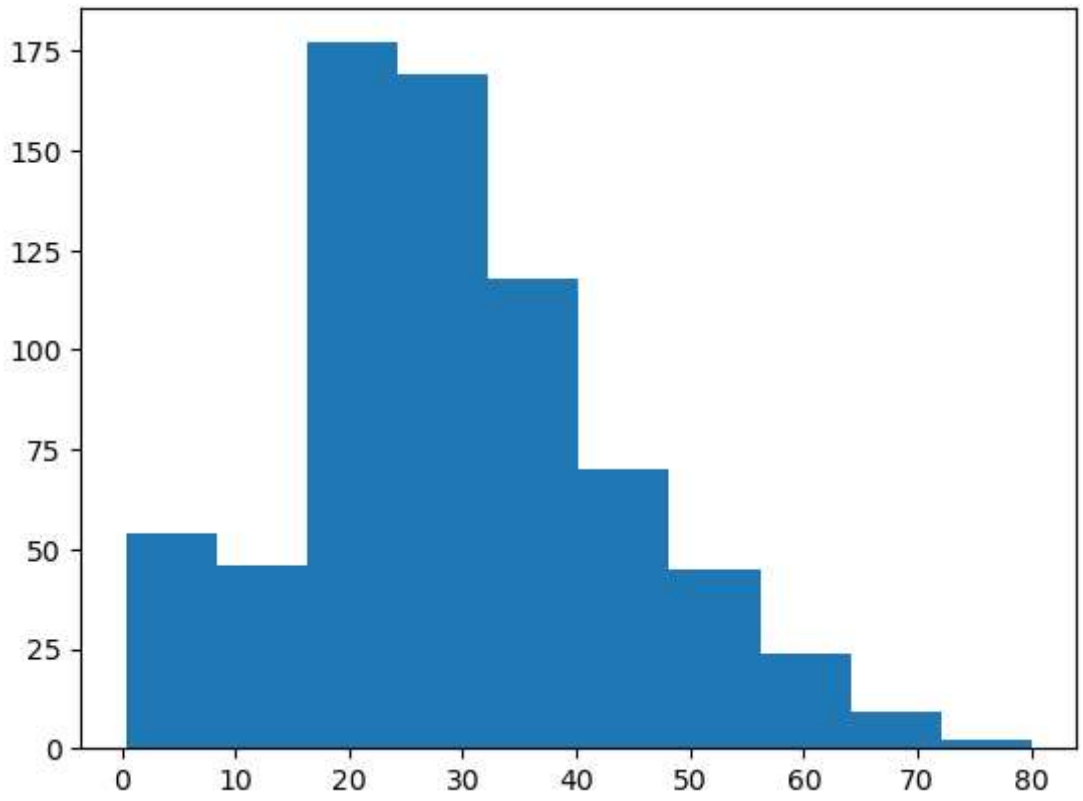
Out[39]:
```
0.38910778230082704
```

In [40]:
```
data_train_mod['Age'].kurt()
```

Out[40]:
```
0.17827415364210353
```

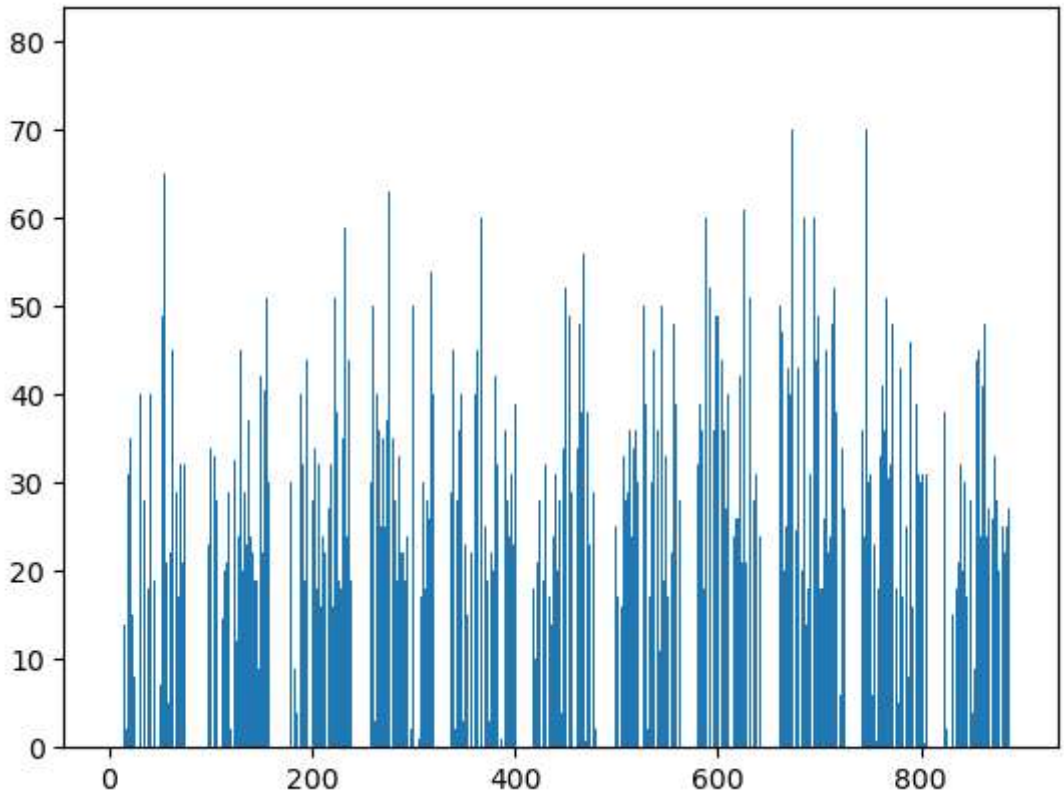
In [41]:
```
plt.hist(data_train_mod['Age'])
```

Out[41]:
```
(array([ 54.,  46., 177., 169., 118.,  70.,  45.,  24.,   9.,   2.]),
 array([ 0.42 ,  8.378, 16.336, 24.294, 32.252, 40.21 , 48.168, 56.126,
        64.084, 72.042, 80.   ]),
 <BarContainer object of 10 artists>)
```



In [42]:
```
plt.bar(height = data_train_mod['Age'], x = np.arange(1,892,1))
```

Out[42]:
```
<BarContainer object of 891 artists>
```



In [43]:
```
import scipy.stats as stats
import pylab
stats.probplot(data_train_mod['Age'], dist ='norm', plot =pylab)
```

Out[43]:
```
((array([-3.16416595e+00, -2.89636677e+00, -2.74675222e+00, -2.64114608e+00,
         -2.55870259e+00, -2.49067391e+00, -2.43252738e+00, -2.38160005e+00,
         -2.33618969e+00, -2.29513992e+00, -2.25762808e+00, -2.22304736e+00,
         -2.19093694e+00, -2.16093830e+00, -2.13276686e+00, -2.10619283e+00,
         -2.08102787e+00, -2.05711563e+00, -2.03432484e+00, -2.01254418e+00,
         -1.99167841e+00, -1.97164537e+00, -1.95237369e+00, -1.93380097e+00,
         -1.91587229e+00, -1.89853909e+00, -1.88175821e+00, -1.86549107e+00,
         -1.84970311e+00, -1.83436318e+00, -1.81944313e+00, -1.80491744e+00,
         -1.79076290e+00, -1.77695830e+00, -1.76348425e+00, -1.75032296e+00,
         -1.73745806e+00, -1.72487445e+00, -1.71255819e+00, -1.70049636e+00,
         -1.68867698e+00, -1.67708890e+00, -1.66572174e+00, -1.65456583e+00,
         -1.64361212e+00, -1.63285214e+00, -1.62227795e+00, -1.61188210e+00,
         -1.60165759e+00, -1.59159783e+00, -1.58169661e+00, -1.57194806e+00,
         -1.56234666e+00, -1.55288715e+00, -1.54356460e+00, -1.53437430e+00,
         -1.52531180e+00, -1.51637287e+00, -1.50755349e+00, -1.49884983e+00,
         -1.49025825e+00, -1.48177530e+00, -1.47339765e+00, -1.46512215e+00,
         -1.45694579e+00, -1.44886569e+00, -1.44087909e+00, -1.43298336e+00,
         -1.42517596e+00, -1.41745449e+00, -1.40981661e+00, -1.40226010e+00,
         -1.39478282e+00, -1.38738272e+00, -1.38005783e+00, -1.37280624e+00,
```

5 -SibSp - Numerical - Discrete Variable

In [44]:
```
data_train_mod['SibSp'].mode()
```

Out[44]:
```
0    0
Name: SibSp, dtype: int64
```

In [45]:
```
data_train_mod['SibSp'].min()
```

Out[45]:
```
0
```

In [46]:
```
data_train_mod['SibSp'].max()
```

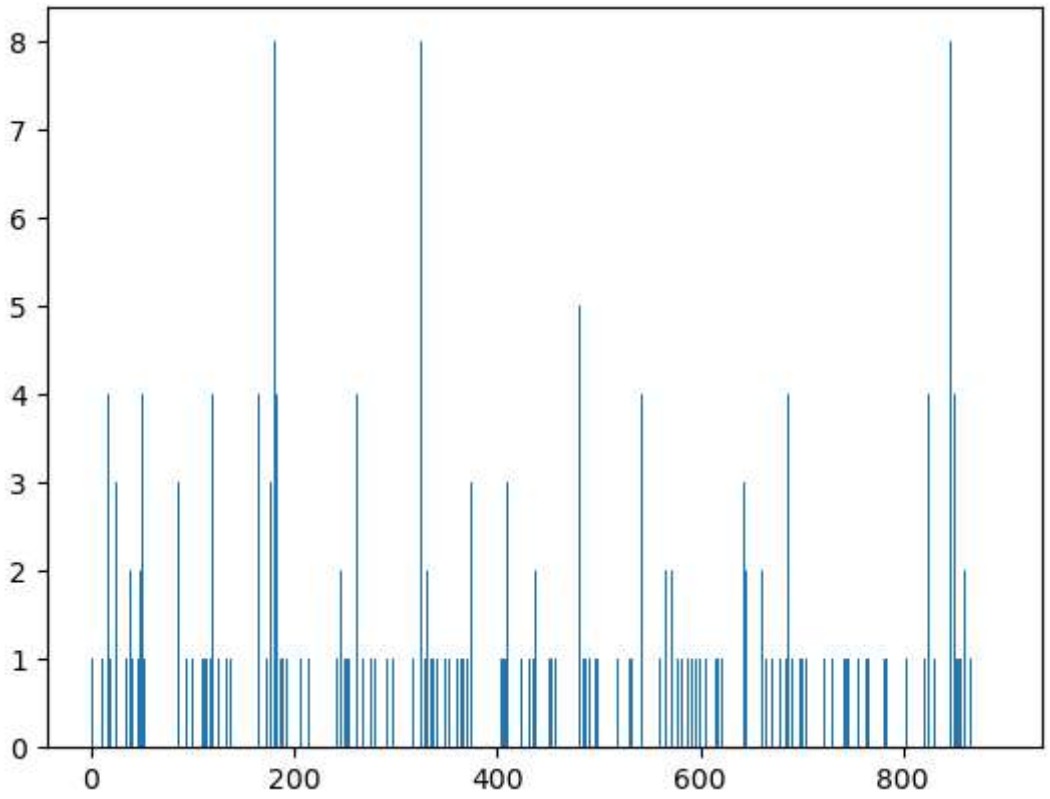
Out[46]:
```
8
```

In [47]:
```
data_train_mod['SibSp'].max() - data_train_mod['SibSp'].min()
```

Out[47]:
```
8
```

In [48]:
```
plt.bar(height = data_train_mod['SibSp'], x = np.arange(1,892,1))
```

Out[48]:
```
<BarContainer object of 891 artists>
```



6 -SibSp - Numerical - Discrete Variable

In [49]:
```
data_train_mod['Parch'].mode()
```

Out[49]:
```
0    0
Name: Parch, dtype: int64
```

In [50]:
```
data_train_mod['Parch'].min()
```

Out[50]:
```
0
```

In [51]:
```
data_train_mod['Parch'].max()
```

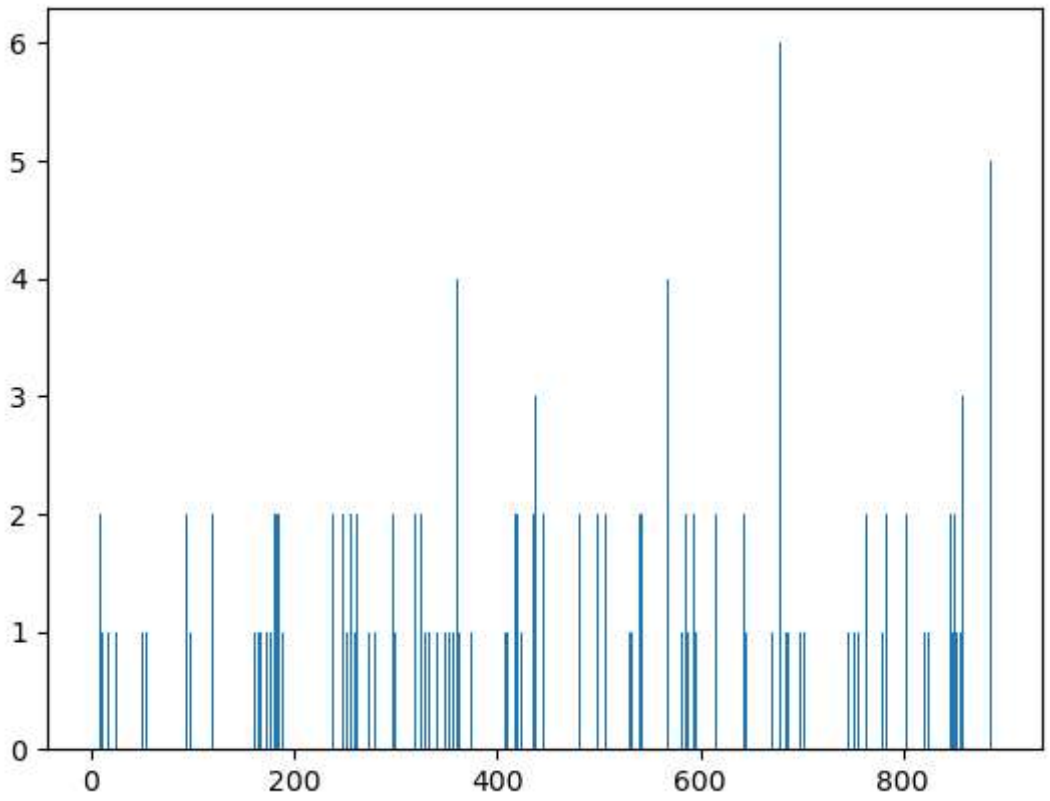
Out[51]: 6

In [52]:
```
data_train_mod['Parch'].max() - data_train_mod['Parch'].min()
```

Out[52]: 6

In [53]:
```
plt.bar(height = data_train_mod['Parch'], x = np.arange(1,892,1))
```

Out[53]: <BarContainer object of 891 artists>



7 - Fare - Numerical Continuos Variable

In [54]:
```
data_train_mod['Fare'].mean()
```

Out[54]: 32.2042079685746

In [55]:
```
data_train_mod['Fare'].median()
```

Out[55]: 14.4542

In [56]:
```
data_train_mod['Fare'].mode()
```

Out[56]:
```
0    8.05
Name: Fare, dtype: float64
```

In [57]:
```
data_train_mod['Fare'].var()
```

Out[57]: 2469.436845743117

In [58]:
```
data_train_mod['Fare'].std()
```

Out[58]: 49.693428597180905

In [59]:
```
data_train_mod['Fare'].min()
```

Out[59]: 0.0

In [60]:
```
data_train_mod['Fare'].max()
```

Out[60]: 512.3292

In [61]:
```
data_train_mod['Fare'].max() - data_train_mod['Fare'].min()
```

Out[61]: 512.3292

In [62]:
```
data_train_mod['Fare'].skew()
```

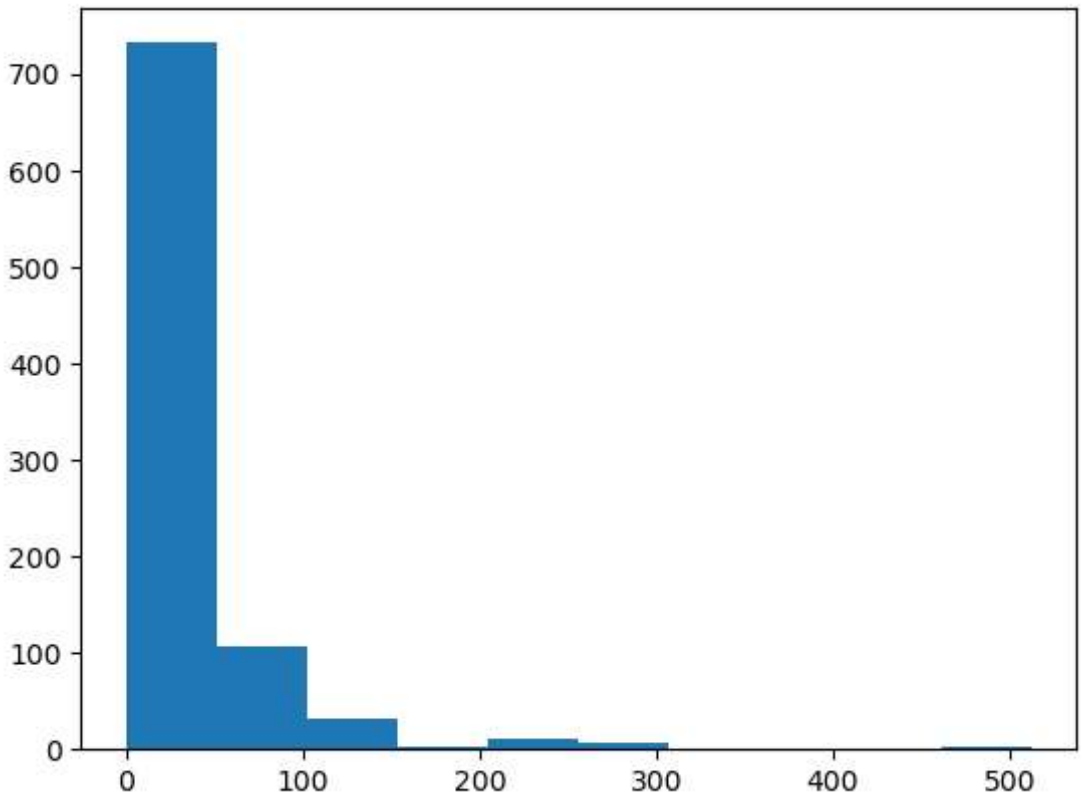
Out[62]: 4.787316519674893

In [63]:
```
data_train_mod['Fare'].kurt()
```

Out[63]: 33.39814088089868

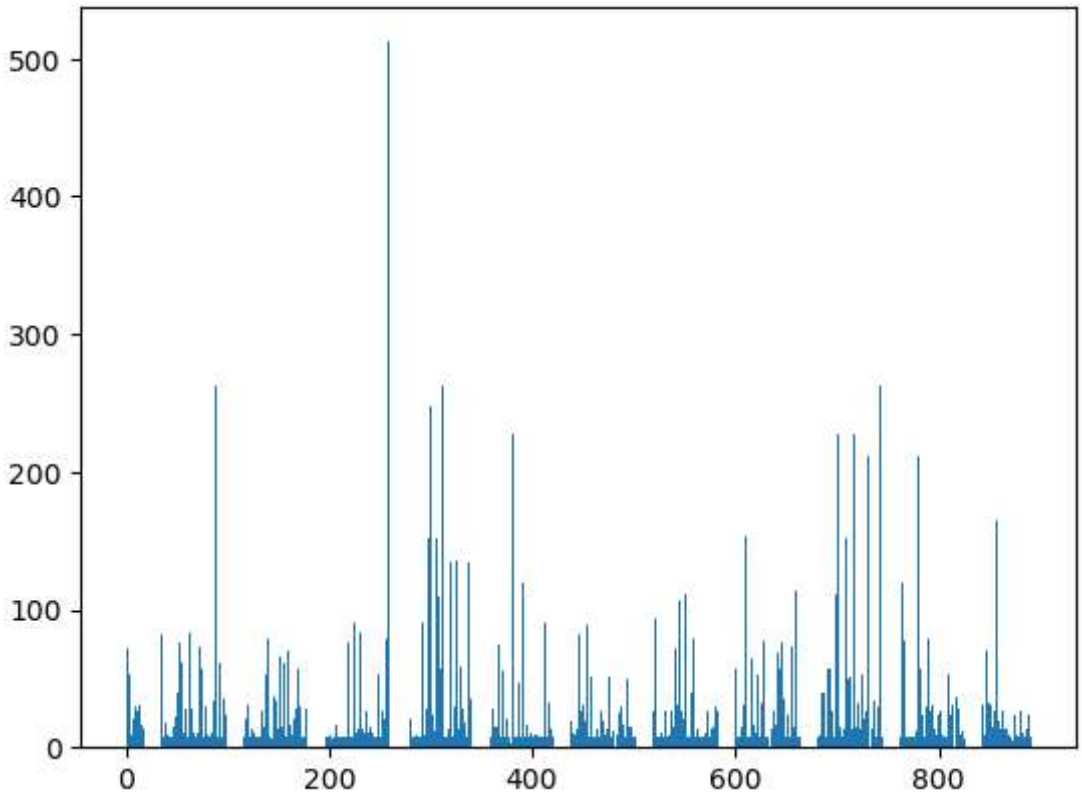
In [64]:
```
plt.hist(data_train_mod['Fare'])
```

Out[64]:
```
(array([732., 106.,  31.,   2.,  11.,   6.,   0.,   0.,   0.,   3.]),
 array([  0.     ,  51.23292, 102.46584, 153.69876, 204.93168, 256.1646 ,
        307.39752, 358.63044, 409.86336, 461.09628, 512.3292 ]),
 <BarContainer object of 10 artists>)
```



In [65]:
```
plt.bar(height = data_train_mod['Fare'], x = np.arange(1,892,1))
```

Out[65]:
```
<BarContainer object of 891 artists>
```



In [66]:
```
stats.probplot(data_train_mod['Fare'], dist ='norm', plot =pylab)
```

Out[66]:
```
((array([-3.16416595e+00, -2.89636677e+00, -2.74675222e+00, -2.64114608e+00,
         -2.55870259e+00, -2.49067391e+00, -2.43252738e+00, -2.38160005e+00,
         -2.33618969e+00, -2.29513992e+00, -2.25762808e+00, -2.22304736e+00,
         -2.19093694e+00, -2.16093830e+00, -2.13276686e+00, -2.10619283e+00,
         -2.08102787e+00, -2.05711563e+00, -2.03432484e+00, -2.01254418e+00,
         -1.99167841e+00, -1.97164537e+00, -1.95237369e+00, -1.93380097e+00,
         -1.91587229e+00, -1.89853909e+00, -1.88175821e+00, -1.86549107e+00,
         -1.84970311e+00, -1.83436318e+00, -1.81944313e+00, -1.80491744e+00,
         -1.79076290e+00, -1.77695830e+00, -1.76348425e+00, -1.75032296e+00,
         -1.73745806e+00, -1.72487445e+00, -1.71255819e+00, -1.70049636e+00,
         -1.68867698e+00, -1.67708890e+00, -1.66572174e+00, -1.65456583e+00,
         -1.64361212e+00, -1.63285214e+00, -1.62227795e+00, -1.61188210e+00,
         -1.60165759e+00, -1.59159783e+00, -1.58169661e+00, -1.57194806e+00,
         -1.56234666e+00, -1.55288715e+00, -1.54356460e+00, -1.53437430e+00,
         -1.52531180e+00, -1.51637287e+00, -1.50755349e+00, -1.49884983e+00,
         -1.49025825e+00, -1.48177530e+00, -1.47339765e+00, -1.46512215e+00,
         -1.45694579e+00, -1.44886569e+00, -1.44087909e+00, -1.43298336e+00,
         -1.42517596e+00, -1.41745449e+00, -1.40981661e+00, -1.40226010e+00,
         -1.39478282e+00, -1.38738272e+00, -1.38005783e+00, -1.37280624e+00,
```

Data Preprocessing Step

1) Missing values
Two Columns have Missing values

In [67]:
```
data_train_mod.isna().sum() # Age has 177 missing values & Embarked has 2 missing
```

Out[67]:
```
Survived         0
PassengerId      0
Pclass           0
Sex              0
Age            177
SibSp            0
Parch            0
Fare             0
Embarked         2
dtype: int64
```

Treating missing values in age column

In [68]:
```
df = data_train_mod[data_train_mod['Age'].isnull()]
```

In [69]:
```
df.Survived.value_counts() # 122 not survived and 52 survived in the missing valu
```

Out[69]:
```
0    125
1     52
Name: Survived, dtype: int64
```

In [70]:
```
df.Pclass.value_counts()  # 136 3rd class and 30 - 1st class and 11 - 2nd class i
```

Out[70]:
```
3    136
1     30
2     11
Name: Pclass, dtype: int64
```

In [71]:
```
df.Sex.value_counts() # 124 male and 53 female in missing values w.r.to Age
```

Out[71]:
```
male      124
female     53
Name: Sex, dtype: int64
```

In [72]:
```
df.Embarked.value_counts() # S - 90, Q - 49, C - 38 in missing values data w.rto
```

Out[72]:
```
S    90
Q    49
C    38
Name: Embarked, dtype: int64
```

the data which is missing is mostly in 3rd class, male, not - survived and from S - Class only
By filling the mean of Age which are male, 3rdclass,not-survived and From S - Class we can get the approx right data

In [73]:
```
df1 = data_train_mod[data_train_mod['Pclass'] == 3]
```

In [74]:
```
df1 = df1[df1['Survived'] == 0]
```

In [75]:
```
df1 = df1[df1['Sex'] == 'male']
```

In [76]:
```
df1 = df1[df1['Embarked'] == 'S']
```

Filling the mean of Age which are male and 3rdclass and not-survived

In [77]:
```
data_train_mod['Age'] = data_train_mod['Age'].fillna(df1['Age'].mean()) # For tro
```

Treating missing values of Embarked Column
Since there are only 2 missing vales we can simply use mode of that column

In [78]:
```
data_train_mod['Embarked'] = data_train_mod['Embarked'].fillna(data_train_mod['Er
```

2) Checking for Duplicate values

In [79]:
```
sum(data_train_mod.duplicated()) # 0 Duplicate rows are present
```

Out[79]:
```
0
```

Checking for Outliers

In [80]:
```
def detect_outliers(df,col):
        # 1st quartile (25%)
        Q1 = np.percentile(df[col], 25)
        # 3rd quartile (75%)
        Q3 = np.percentile(df[col],75)
        # Interquartile range (IQR)
        IQR = Q3 - Q1
        upper_limit = Q3 + 1.5*IQR
        lower_limit = Q1 - 1.5*IQR
        outliers = np.where(df[col] > upper_limit, True, np.where(df[col] < lower
        return sum(outliers)


def outlier_treatment(df,col):
        # 1st quartile (25%)
        Q1 = np.percentile(df[col], 25)
        # 3rd quartile (75%)
        Q3 = np.percentile(df[col],75)
        # Interquartile range (IQR)
        IQR = Q3 - Q1
        upper_limit = Q3 + 1.5*IQR
        lower_limit = Q1 - 1.5*IQR
        df[col] = np.where(df[col] > upper_limit, upper_limit, np.where(df[col] <
        return df[col]
```

In [81]:
```
detect_outliers(data_train_mod, 'Age') # 66 outliers are present
```

Out[81]:
```
66
```

In [82]:
```
outlier_treatment(data_train_mod, 'Age')
```

Out[82]:
```
0      22.000000
1      38.000000
2      26.000000
3      35.000000
4      35.000000
         ...
886    27.000000
887    19.000000
888    27.168478
889    26.000000
890    32.000000
Name: Age, Length: 891, dtype: float64
```

In [83]:
```
detect_outliers(data_train_mod, 'Fare') # 116 outliers are present
```

Out[83]:
```
116
```

In [84]:
```
outlier_treatment(data_train_mod, 'Fare')
```

Out[84]:
```
0       7.2500
1      65.6344
2       7.9250
3      53.1000
4       8.0500
         ...
886    13.0000
887    30.0000
888    23.4500
889    30.0000
890     7.7500
Name: Fare, Length: 891, dtype: float64
```

In [85]:
```
des = data_train_mod.describe() # Checking the descriptive Analysis after Treatir
```

3) Converting Non - Numerical Features to Numerical

The Non - Numerical Features are :

In [86]:
```
                                    # 1) Sex - Nominal
                                    # 2) Embarked - Nominal
# Converting Sex column Using oneHot encoding
data_train_mod = pd.get_dummies(data_train_mod, columns = ['Sex'])
```

Embarked Column

In [87]:
```
data_train_mod = pd.get_dummies(data_train_mod, columns = ['Embarked'])

# 4) Checking whether the data is normally distributed or not for Continuos Varia
stats.probplot(data_train_mod['Age'], dist ='norm', plot =pylab) # data is mostly
```

Out[87]:
```
((array([-3.16416595e+00, -2.89636677e+00, -2.74675222e+00, -2.64114608e+00,
         -2.55870259e+00, -2.49067391e+00, -2.43252738e+00, -2.38160005e+00,
         -2.33618969e+00, -2.29513992e+00, -2.25762808e+00, -2.22304736e+00,
         -2.19093694e+00, -2.16093830e+00, -2.13276686e+00, -2.10619283e+00,
         -2.08102787e+00, -2.05711563e+00, -2.03432484e+00, -2.01254418e+00,
         -1.99167841e+00, -1.97164537e+00, -1.95237369e+00, -1.93380097e+00,
         -1.91587229e+00, -1.89853909e+00, -1.88175821e+00, -1.86549107e+00,
         -1.84970311e+00, -1.83436318e+00, -1.81944313e+00, -1.80491744e+00,
         -1.79076290e+00, -1.77695830e+00, -1.76348425e+00, -1.75032296e+00,
         -1.73745806e+00, -1.72487445e+00, -1.71255819e+00, -1.70049636e+00,
         -1.68867698e+00, -1.67708890e+00, -1.66572174e+00, -1.65456583e+00,
         -1.64361212e+00, -1.63285214e+00, -1.62227795e+00, -1.61188210e+00,
         -1.60165759e+00, -1.59159783e+00, -1.58169661e+00, -1.57194806e+00,
         -1.56234666e+00, -1.55288715e+00, -1.54356460e+00, -1.53437430e+00,
         -1.52531180e+00, -1.51637287e+00, -1.50755349e+00, -1.49884983e+00,
         -1.49025825e+00, -1.48177530e+00, -1.47339765e+00, -1.46512215e+00,
         -1.45694579e+00, -1.44886569e+00, -1.44087909e+00, -1.43298336e+00,
         -1.42517596e+00, -1.41745449e+00, -1.40981661e+00, -1.40226010e+00,
         -1.39478282e+00, -1.38738272e+00, -1.38005783e+00, -1.37280624e+00,
```

In [88]:
```
stats.probplot(data_train_mod['Fare'], dist ='norm', plot =pylab)
```

Out[88]:
```
((array([-3.16416595e+00, -2.89636677e+00, -2.74675222e+00, -2.64114608e+00,
         -2.55870259e+00, -2.49067391e+00, -2.43252738e+00, -2.38160005e+00,
         -2.33618969e+00, -2.29513992e+00, -2.25762808e+00, -2.22304736e+00,
         -2.19093694e+00, -2.16093830e+00, -2.13276686e+00, -2.10619283e+00,
         -2.08102787e+00, -2.05711563e+00, -2.03432484e+00, -2.01254418e+00,
         -1.99167841e+00, -1.97164537e+00, -1.95237369e+00, -1.93380097e+00,
         -1.91587229e+00, -1.89853909e+00, -1.88175821e+00, -1.86549107e+00,
         -1.84970311e+00, -1.83436318e+00, -1.81944313e+00, -1.80491744e+00,
         -1.79076290e+00, -1.77695830e+00, -1.76348425e+00, -1.75032296e+00,
         -1.73745806e+00, -1.72487445e+00, -1.71255819e+00, -1.70049636e+00,
         -1.68867698e+00, -1.67708890e+00, -1.66572174e+00, -1.65456583e+00,
         -1.64361212e+00, -1.63285214e+00, -1.62227795e+00, -1.61188210e+00,
         -1.60165759e+00, -1.59159783e+00, -1.58169661e+00, -1.57194806e+00,
         -1.56234666e+00, -1.55288715e+00, -1.54356460e+00, -1.53437430e+00,
         -1.52531180e+00, -1.51637287e+00, -1.50755349e+00, -1.49884983e+00,
         -1.49025825e+00, -1.48177530e+00, -1.47339765e+00, -1.46512215e+00,
         -1.45694579e+00, -1.44886569e+00, -1.44087909e+00, -1.43298336e+00,
         -1.42517596e+00, -1.41745449e+00, -1.40981661e+00, -1.40226010e+00,
         -1.39478282e+00, -1.38738272e+00, -1.38005783e+00, -1.37280624e+00,
```

In [89]:
```
stats.probplot(np.log(data_train_mod['Fare']), dist ='norm', plot =pylab)
```

```
C:\Users\PC\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: Runtime
Warning: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
C:\Users\PC\anaconda3\lib\site-packages\numpy\lib\function_base.py:2536: Runt
imeWarning: invalid value encountered in subtract
  X -= avg[:, None]
```

In [90]:
```
stats.probplot(np.exp(data_train_mod['Fare']), dist ='norm', plot =pylab)
```

Out[90]:
```
((array([-3.16416595e+00, -2.89636677e+00, -2.74675222e+00, -2.64114608e+00,
         -2.55870259e+00, -2.49067391e+00, -2.43252738e+00, -2.38160005e+00,
         -2.33618969e+00, -2.29513992e+00, -2.25762808e+00, -2.22304736e+00,
         -2.19093694e+00, -2.16093830e+00, -2.13276686e+00, -2.10619283e+00,
         -2.08102787e+00, -2.05711563e+00, -2.03432484e+00, -2.01254418e+00,
         -1.99167841e+00, -1.97164537e+00, -1.95237369e+00, -1.93380097e+00,
         -1.91587229e+00, -1.89853909e+00, -1.88175821e+00, -1.86549107e+00,
         -1.84970311e+00, -1.83436318e+00, -1.81944313e+00, -1.80491744e+00,
         -1.79076290e+00, -1.77695830e+00, -1.76348425e+00, -1.75032296e+00,
         -1.73745806e+00, -1.72487445e+00, -1.71255819e+00, -1.70049636e+00,
         -1.68867698e+00, -1.67708890e+00, -1.66572174e+00, -1.65456583e+00,
         -1.64361212e+00, -1.63285214e+00, -1.62227795e+00, -1.61188210e+00,
         -1.60165759e+00, -1.59159783e+00, -1.58169661e+00, -1.57194806e+00,
         -1.56234666e+00, -1.55288715e+00, -1.54356460e+00, -1.53437430e+00,
         -1.52531180e+00, -1.51637287e+00, -1.50755349e+00, -1.49884983e+00,
         -1.49025825e+00, -1.48177530e+00, -1.47339765e+00, -1.46512215e+00,
         -1.45694579e+00, -1.44886569e+00, -1.44087909e+00, -1.43298336e+00,
         -1.42517596e+00, -1.41745449e+00, -1.40981661e+00, -1.40226010e+00,
         -1.39478282e+00, -1.38738272e+00, -1.38005783e+00, -1.37280624e+00,
```

In [91]:
```
stats.probplot(np.sqrt(data_train_mod['Fare']), dist ='norm', plot =pylab)
```

Out[91]:
```
((array([-3.16416595e+00, -2.89636677e+00, -2.74675222e+00, -2.64114608e+00,
         -2.55870259e+00, -2.49067391e+00, -2.43252738e+00, -2.38160005e+00,
         -2.33618969e+00, -2.29513992e+00, -2.25762808e+00, -2.22304736e+00,
         -2.19093694e+00, -2.16093830e+00, -2.13276686e+00, -2.10619283e+00,
         -2.08102787e+00, -2.05711563e+00, -2.03432484e+00, -2.01254418e+00,
         -1.99167841e+00, -1.97164537e+00, -1.95237369e+00, -1.93380097e+00,
         -1.91587229e+00, -1.89853909e+00, -1.88175821e+00, -1.86549107e+00,
         -1.84970311e+00, -1.83436318e+00, -1.81944313e+00, -1.80491744e+00,
         -1.79076290e+00, -1.77695830e+00, -1.76348425e+00, -1.75032296e+00,
         -1.73745806e+00, -1.72487445e+00, -1.71255819e+00, -1.70049636e+00,
         -1.68867698e+00, -1.67708890e+00, -1.66572174e+00, -1.65456583e+00,
         -1.64361212e+00, -1.63285214e+00, -1.62227795e+00, -1.61188210e+00,
         -1.60165759e+00, -1.59159783e+00, -1.58169661e+00, -1.57194806e+00,
         -1.56234666e+00, -1.55288715e+00, -1.54356460e+00, -1.53437430e+00,
         -1.52531180e+00, -1.51637287e+00, -1.50755349e+00, -1.49884983e+00,
         -1.49025825e+00, -1.48177530e+00, -1.47339765e+00, -1.46512215e+00,
         -1.45694579e+00, -1.44886569e+00, -1.44087909e+00, -1.43298336e+00,
         -1.42517596e+00, -1.41745449e+00, -1.40981661e+00, -1.40226010e+00,
         -1.39478282e+00, -1.38738272e+00, -1.38005783e+00, -1.37280624e+00,
```

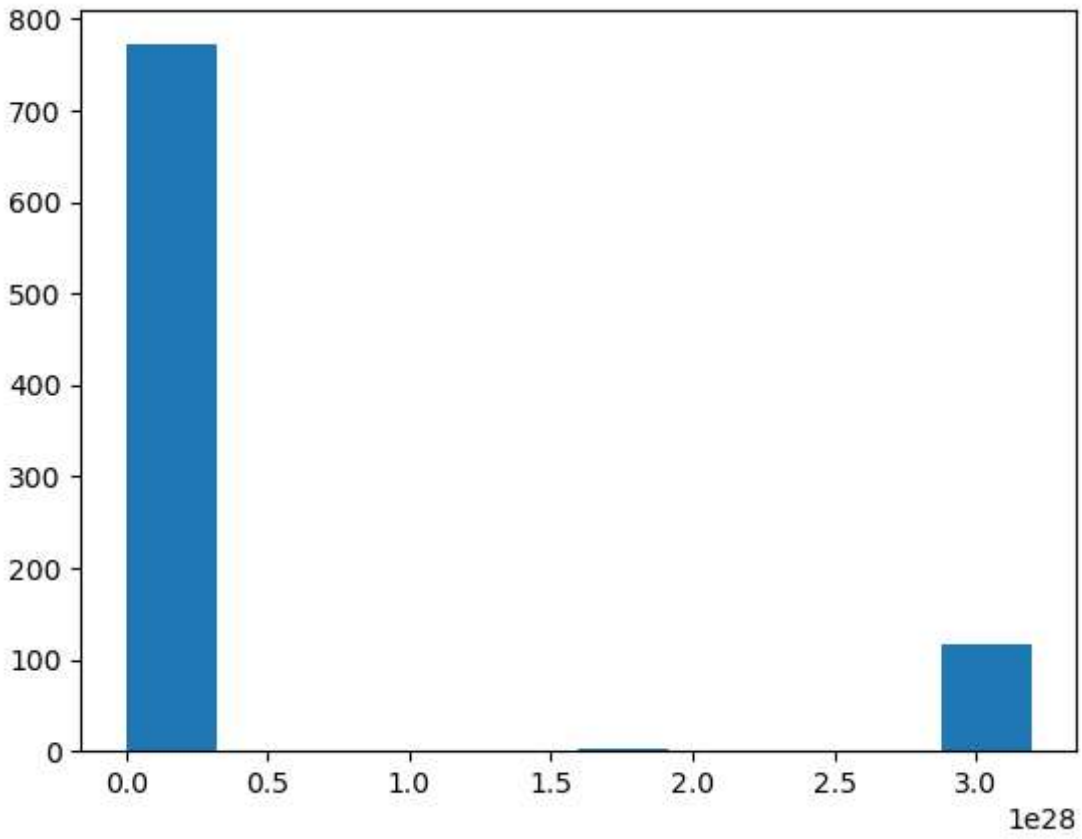
In [92]:
```
stats.probplot(np.reciprocal(data_train_mod['Fare']), dist ='norm', plot =pylab)
```

```
C:\Users\PC\anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarning: divide by zero encountered in reciprocal
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

In [93]:
```
Fare_tr = data_train_mod['Fare'].transform([np.log, np.exp, np.sqrt, np.reciproca
```

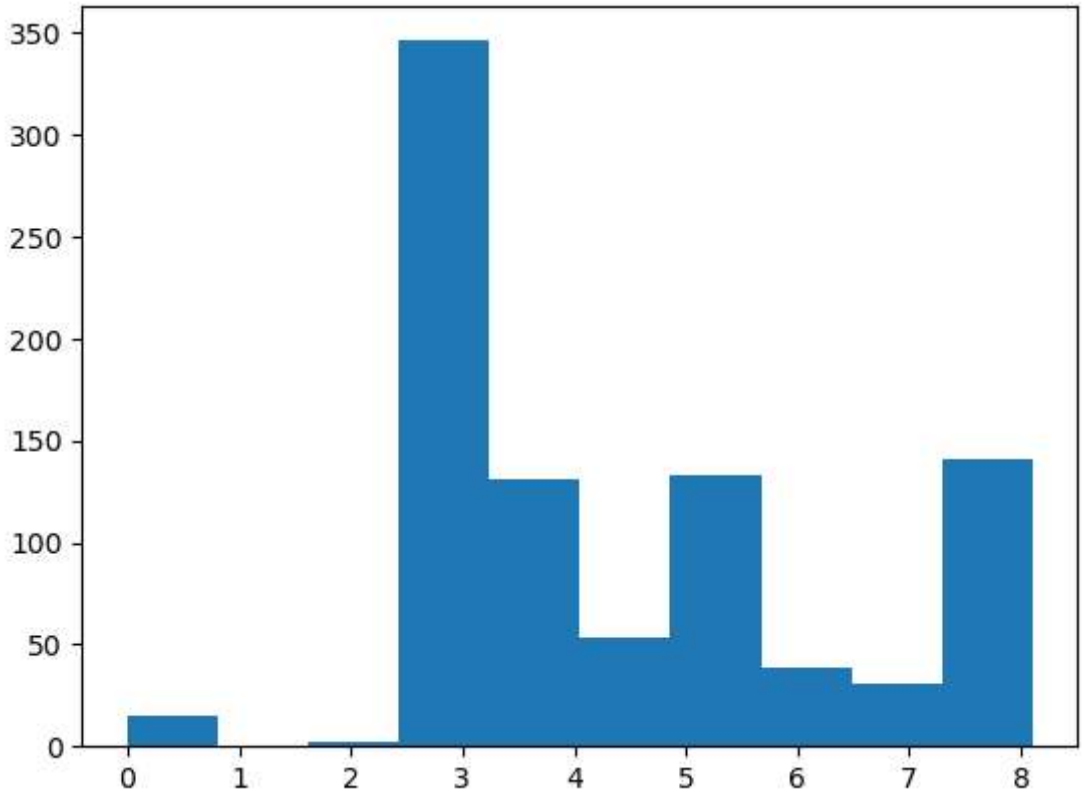
In [94]:
```
plt.hist(Fare_tr['exp'])
```

Out[94]:
```
(array([772.,   1.,   0.,   0.,   0.,   2.,   0.,   0.,   0., 116.]),
 array([1.00000000e+00, 3.19637513e+27, 6.39275026e+27, 9.58912539e+27,
        1.27855005e+28, 1.59818757e+28, 1.91782508e+28, 2.23746259e+28,
        2.55710010e+28, 2.87673762e+28, 3.19637513e+28]),
 <BarContainer object of 10 artists>)
```



In [95]:
```
plt.hist(Fare_tr['sqrt']) # Sqrt transformation seems like appropriate to normal
```

Out[95]:
```
(array([ 15.,   0.,   2., 346., 131.,  53., 133.,  39.,  31., 141.]),
 array([0.        , 0.8101506 , 1.62030121, 2.43045181, 3.24060241,
        4.05075302, 4.86090362, 5.67105422, 6.48120483, 7.29135543,
        8.10150603]),
 <BarContainer object of 10 artists>)
```



In [96]:
```
data_train_mod['Fare'] = data_train_mod['Fare'].transform(np.sqrt)
```

Scaling the data
Using Customized Min-Max Scalor Function

In [97]:
```
def norm_func(i):
    x = (i-i.min())/(i.max() - i.min())
    return x;
```

In [98]:
```
data_train_mod['Age'] = norm_func(data_train_mod['Age'])
```

In [99]:
```
data_train_mod['Fare'] = norm_func(data_train_mod['Fare'])
```

In [100]:
```
des = data_train_mod.describe()
```

Making the dataset Imbalanced to Balanced

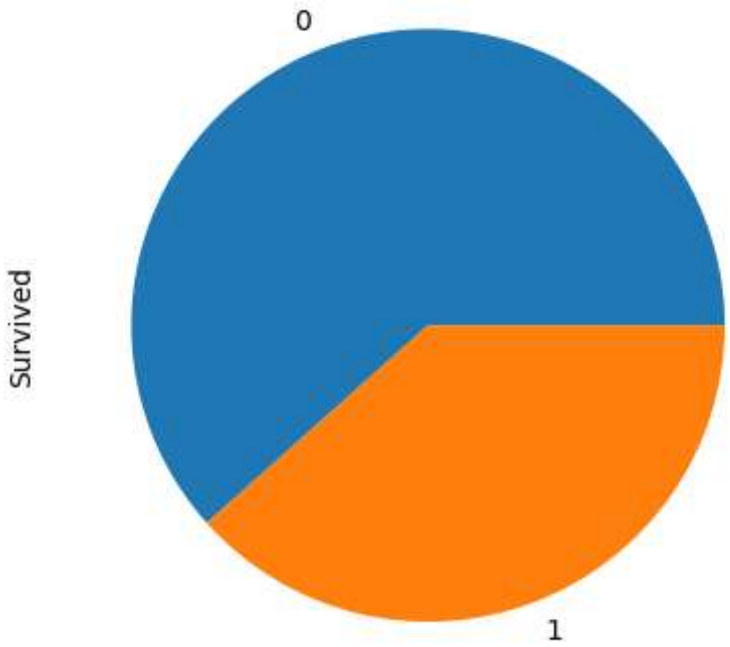
In [101]:
```
X = data_train_mod.iloc[:, 2:]
```

In [102]:
```
y = data_train_mod.iloc[:,:2]
```

Pie Plot before applyting Random UnderSampling

In [103]:
```
y['Survived'].value_counts().plot.pie()
```

Out[103]:
```
<AxesSubplot:ylabel='Survived'>
```



conda install -c conda-forge imbalanced-learn

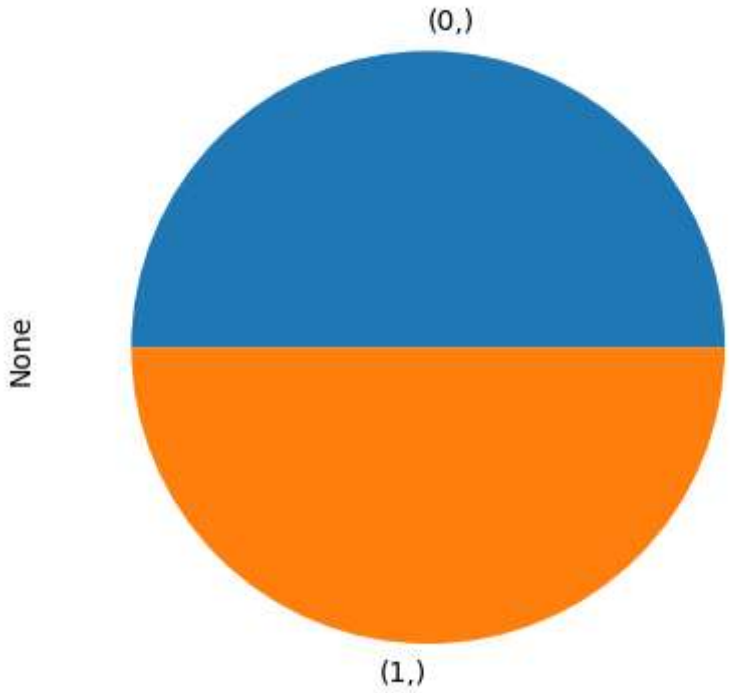
In [107]:
```
from collections import Counter
from sklearn.datasets import make_classification
from imblearn.under_sampling import RandomUnderSampler
rus = RandomUnderSampler(sampling_strategy = 'not minority')
```

In [108]:
```
X_res, y_res = rus.fit_resample(X, y['Survived'])
```

In [109]:
```
y_res = pd.DataFrame(y_res)
```

In [110]:
```
y_res.value_counts().plot.pie()
```

Out[110]:
```
<AxesSubplot:ylabel='None'>
```



Data Preprocessing on Test Data set

In [111]:
```
data_test_mod.isna().sum() # Age column has  86 missing values on test dataset &
```

Out[111]:
```
PassengerId     0
Pclass          0
Sex             0
Age            86
SibSp           0
Parch           0
Fare            1
Embarked        0
dtype: int64
```

Treating missing values in age column

In [112]:
```
df = data_test_mod[data_test_mod['Age'].isnull()]
```

In [113]:
```
df.Pclass.value_counts()  # 72  3rd class and 9 - 1st class and 5 - 2nd class in
```

Out[113]:
```
3    72
1     9
2     5
Name: Pclass, dtype: int64
```

In [114]:
```
df.Sex.value_counts() # 61 male and 25 female in missing values w.r.to Age
```

Out[114]:
```
male      61
female    25
Name: Sex, dtype: int64
```

In [115]:
```
df.Embarked.value_counts() # S - 42, Q - 24, C - 20 in missing values data w.rto
```

Out[115]:
```
S    42
Q    24
C    20
Name: Embarked, dtype: int64
```

the data which is missing is mostly in 3rd class, male,from S - Class only
By filling the mean of Age which are male, 3rdclass, From S - Class we can get the approx right data

In [116]:
```
df1 = data_test_mod[data_test_mod['Pclass'] == 3]
```

In [117]:
```
df1 = df1[df1['Sex'] == 'male']
```

In [118]:
```
df1 = df1[df1['Embarked'] == 'S']
```

Filling the mean of Age which are male and 3rdclass and not-survived

In [119]:
```
data_test_mod['Age'] = data_test_mod['Age'].fillna(df1['Age'].mean()) # For trai
```

Treating missing values of Fare Column
Since there are only 1 missing vales we can simply use mode of that column

In [120]:
```
data_test_mod['Fare'] = data_test_mod['Fare'].fillna(data_test_mod['Fare'].mean()
```

2) Checking for Duplicate values

In [121]:
```
sum(data_test_mod.duplicated()) # 0 Duplicate rows are present
```

Out[121]:
```
0
```

Checking for Outliers

In [122]:
```
detect_outliers(data_test_mod, 'Age') # 36  outliers are present
```

Out[122]:
```
36
```

In [123]:
```
outlier_treatment(data_test_mod, 'Age')
```

Out[123]:
```
0      34.500000
1      47.000000
2      54.875000
3      27.000000
4      22.000000
         ...
413    24.939605
414    39.000000
415    38.500000
416    24.939605
417    24.939605
Name: Age, Length: 418, dtype: float64
```

In [124]:
```
detect_outliers(data_test_mod, 'Fare') # 55 outliers are present
```

Out[124]:
```
55
```

In [125]:
```
outlier_treatment(data_test_mod, 'Fare')
```

Out[125]:
```
0       7.8292
1       7.0000
2       9.6875
3       8.6625
4      12.2875
         ...
413     8.0500
414    66.9063
415     7.2500
416     8.0500
417    22.3583
Name: Fare, Length: 418, dtype: float64
```

In [126]:
```
des_test = data_test_mod.describe()
```

3) Converting Non - Numerical Features to Numerical
The Non - Numerical Features are :

In [127]:
```
                                    # 1) Sex - Nominal
                                    # 2) Embarked - Nominal
# Converting Sex column Using oneHot encoding
data_test_mod = pd.get_dummies(data_test_mod, columns = ['Sex'])
```

Embarked Column

In [128]:
```
data_test_mod = pd.get_dummies(data_test_mod, columns = ['Embarked'])

# 4) Checking whether the data is normally distributed or not for Continuos Varia
stats.probplot(data_test_mod['Age'], dist ='norm', plot =pylab) # data is mostly
```

Out[128]:
```
((array([-2.93702766, -2.6502503 , -2.48862734, -2.37383857, -2.28377496,
         -2.20913468, -2.14508828, -2.08879364, -2.03843131, -1.99276366,
         -1.95090921, -1.91221703, -1.87619232, -1.84244974, -1.81068319,
         -1.78064526, -1.75213303, -1.72497793, -1.69903832, -1.674194  ,
         -1.65034206, -1.6273937 , -1.60527171, -1.58390852, -1.56324469,
         -1.54322758, -1.5238104 , -1.50495131, -1.48661278, -1.468761  ,
         -1.4513654 , -1.43439822, -1.41783423, -1.40165035, -1.38582549,
         -1.37034025, -1.35517682, -1.34031874, -1.32575079, -1.3114589 ,
         -1.29742997, -1.28365184, -1.27011319, -1.25680341, -1.24371263,
         -1.23083159, -1.21815159, -1.20566447, -1.19336258, -1.18123868,
         -1.16928597, -1.15749802, -1.14586875, -1.13439242, -1.12306358,
         -1.11187708, -1.10082801, -1.08991172, -1.07912379, -1.06846   ,
         -1.05791635, -1.04748902, -1.03717435, -1.02696887, -1.01686924,
         -1.00687229, -0.99697496, -0.98717434, -0.97746763, -0.96785216,
         -0.95832535, -0.94888473, -0.93952794, -0.93025269, -0.92105678,
         -0.91193811, -0.90289465, -0.89392443, -0.88502557, -0.87619625,
         -0.86743471, -0.85873926, -0.85010826, -0.84154013, -0.83303333,
         -0.8245864 , -0.8161979 , -0.80786644, -0.79959068, -0.79136933,
         -0.78320112, -0.77508484, -0.76701929, -0.75900334, -0.75103586,
```

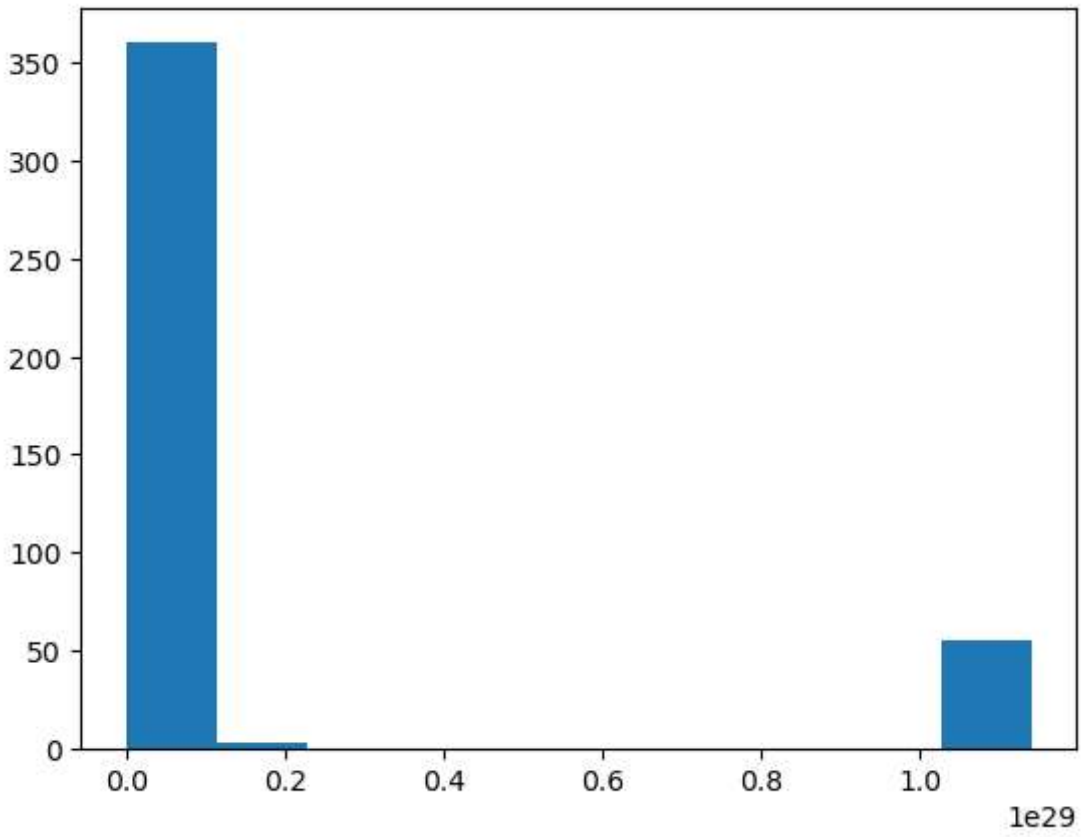
In [129]:
```
stats.probplot(data_test_mod['Fare'], dist ='norm', plot =pylab)
```

Out[129]:
```
((array([-2.93702766, -2.6502503 , -2.48862734, -2.37383857, -2.28377496,
         -2.20913468, -2.14508828, -2.08879364, -2.03843131, -1.99276366,
         -1.95090921, -1.91221703, -1.87619232, -1.84244974, -1.81068319,
         -1.78064526, -1.75213303, -1.72497793, -1.69903832, -1.674194  ,
         -1.65034206, -1.6273937 , -1.60527171, -1.58390852, -1.56324469,
         -1.54322758, -1.5238104 , -1.50495131, -1.48661278, -1.468761  ,
         -1.4513654 , -1.43439822, -1.41783423, -1.40165035, -1.38582549,
         -1.37034025, -1.35517682, -1.34031874, -1.32575079, -1.3114589 ,
         -1.29742997, -1.28365184, -1.27011319, -1.25680341, -1.24371263,
         -1.23083159, -1.21815159, -1.20566447, -1.19336258, -1.18123868,
         -1.16928597, -1.15749802, -1.14586875, -1.13439242, -1.12306358,
         -1.11187708, -1.10082801, -1.08991172, -1.07912379, -1.06846   ,
         -1.05791635, -1.04748902, -1.03717435, -1.02696887, -1.01686924,
         -1.00687229, -0.99697496, -0.98717434, -0.97746763, -0.96785216,
         -0.95832535, -0.94888473, -0.93952794, -0.93025269, -0.92105678,
         -0.91193811, -0.90289465, -0.89392443, -0.88502557, -0.87619625,
         -0.86743471, -0.85873926, -0.85010826, -0.84154013, -0.83303333,
         -0.8245864 , -0.8161979 , -0.80786644, -0.79959068, -0.79136933,
         -0.78320112, -0.77508484, -0.76701929, -0.75900334, -0.75103586,
```

In [130]:
```
Fare_test_tr = data_test_mod['Fare'].transform([np.log, np.exp, np.sqrt, np.recip
```

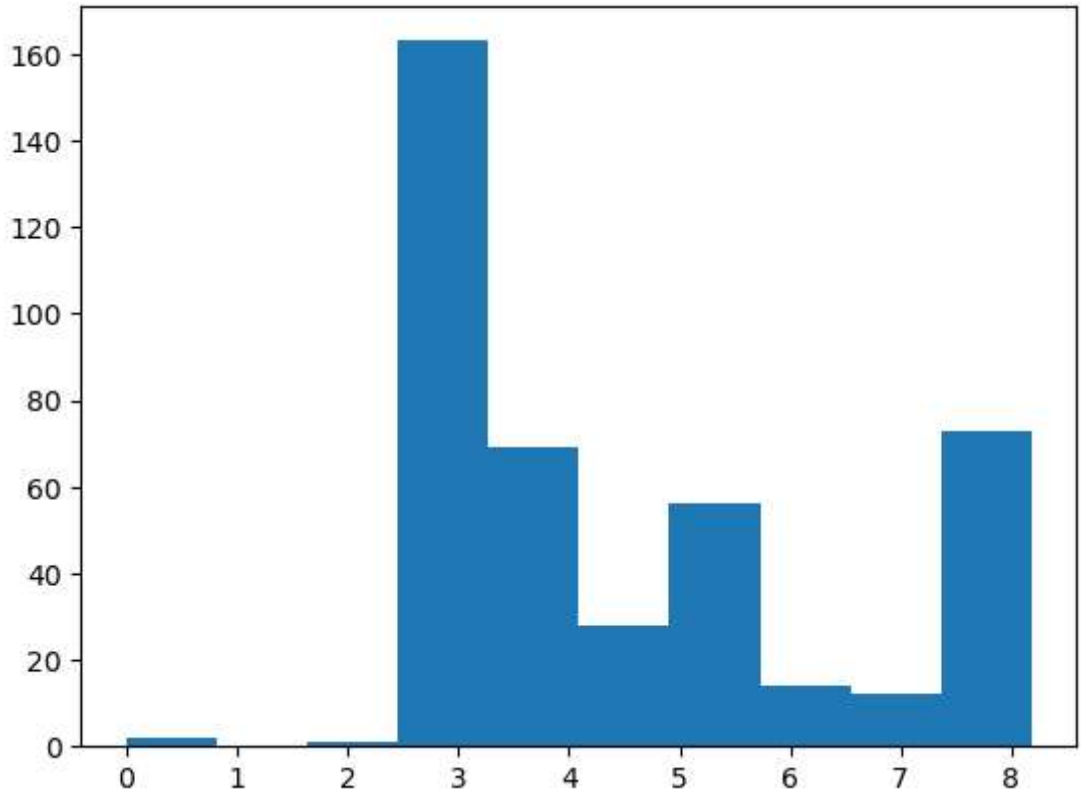
In [131]:
```
plt.hist(Fare_test_tr['exp'])
```

Out[131]:
```
(array([360.,   3.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,  55.]),
 array([1.00000000e+00, 1.14034666e+28, 2.28069332e+28, 3.42103998e+28,
        4.56138664e+28, 5.70173330e+28, 6.84207996e+28, 7.98242661e+28,
        9.12277327e+28, 1.02631199e+29, 1.14034666e+29]),
 <BarContainer object of 10 artists>)
```



In [132]:
```
plt.hist(Fare_test_tr['sqrt']) # Sqrt transformation seems like appropriate to no
```

Out[132]:
```
(array([  2.,   0.,   1., 163.,  69.,  28.,  56.,  14.,  12.,  73.]),
 array([0.        , 0.81796271, 1.63592543, 2.45388814, 3.27185085,
        4.08981357, 4.90777628, 5.72573899, 6.5437017 , 7.36166442,
        8.17962713]),
 <BarContainer object of 10 artists>)
```



In [133]:
```
data_test_mod['Fare'] = data_test_mod['Fare'].transform(np.sqrt)
```

Scaling the data

Using Customized Min-Max Scalor Function

In [134]:
```
data_test_mod['Age'] = norm_func(data_test_mod['Age'])
```

In [135]:
```
data_test_mod['Fare'] = norm_func(data_test_mod['Fare'])
```

In [136]:
```
des_test = data_test_mod.describe()
```

Applying Decision Tree Algorithm
Splitting the Input data

In [137]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X_res,y_res, test_size = 0.1)
```

In [138]:
```
sum(y_train['Survived'])/len(y_train['Survived']) # 49.7 %
```

Out[138]:
```
0.4959349593495935
```

In [139]:
```
sum(y_test['Survived'])/len(y_test['Survived']) # 52.1% - # Data is splitted Balc
```

Out[139]:
```
0.5362318840579711
```

In [140]:
```
from sklearn.tree import DecisionTreeClassifier as DT
```

By the GridSearchCV I have chosen the Best Parameters and Building a model Based on that

In [141]:
```
final_model = DT(max_depth =  10, min_samples_leaf = 10, max_features = 'log2')
```

Training the model

In [142]:
```
final_model.fit(X_train, y_train)
```

Out[142]:
```
DecisionTreeClassifier(max_depth=10, max_features='log2', min_samples_leaf=10)
```

Prediction on splitted Test data of Train Dataset

In [143]:
```
pred = final_model.predict(X_test)
```

Cross tab or Confusion matrix

In [144]:
```
pd.crosstab(y_test['Survived'], pred, rownames=['Actual_values'], colnames=['Pred
```

Out[144]:

Predicted_values	0	1
Actual_values		
0	23	9
1	10	27

Accuracy

Accuracy

In [145]:
```
np.mean(pred == y_test['Survived']) # 76.8.5%
```

Out[145]:
```
0.7246376811594203
```

For validation purpose predicting on train data of Train Dataset

In [146]:
```
pred_train = final_model.predict(X_train)
```

Cross tab or Confusion matrix

In [147]:
```
pd.crosstab(y_train['Survived'], pred_train, rownames=['Actual_values'], colnames
```

Out[147]:

Predicted_values	0	1
Actual_values		
0	259	51
1	71	234

Accuracy on Train Data

In [148]:
```
np.mean(pred_train == y_train['Survived']) # 82.6 % - # Model seems fine
```

Out[148]:
```
0.8016260162601626
```

predicting on test dataset

In [149]:
```
pred_final = final_model.predict(data_test_mod.iloc[:,1:])
print('The Predicted values on Test Dataset is :',pred_final)
```

```
The Predicted values on Test Dataset is : [0 1 0 0 1 0 1 1 1 0 0 0 1 0 1 1 0 0
1 1 1 0 1 0 1 0 1 0 0 1 0 0 1 0 1 0 1
 1 0 0 1 0 0 1 1 0 0 0 0 1 1 0 1 1 0 0 0 0 0 1 0 0 0 1 1 1 1 0 0 1 1 0 1 0
 1 0 0 1 0 1 1 1 0 0 0 1 1 1 1 1 1 0 1 0 0 0 1 0 1 0 1 0 0 0 1 0 0 0 0 0 0
 1 1 1 1 1 0 1 0 1 1 0 1 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0
 0 1 1 1 0 1 0 0 1 1 0 1 1 1 1 0 0 0 0 0 1 1 0 0 0 0 0 1 1 1 1 0 0 1 1 0 1
 0 1 0 0 0 0 0 0 0 0 0 0 1 0 1 1 1 1 1 0 0 1 0 1 0 0 0 0 1 1 0 1 1 1 0 1 0
 1 0 0 1 0 1 0 0 0 1 0 0 1 0 1 0 1 1 0 1 1 0 0 1 1 1 1 1 1 0 1 0 0 0 0 0 1
 0 0 0 1 1 0 0 0 0 1 0 0 0 1 1 0 1 0 0 0 0 1 1 1 1 1 0 0 1 0 0 0 1 0 1 0 0
 1 1 0 0 0 0 0 0 1 1 1 1 1 1 0 0 0 1 0 1 1 0 0 0 0 0 0 0 1 0 1 0 0 0 1 0 0
 1 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 1 1 0 0 1 1 0 1 0 0 1 0 1 1 0 1 0 1 0 1 0
 0 1 0 0 1 1 1 0 0 1 0 0 1 1 0 1 0 0 0 1 0 0 0 0 0 1 0 1 0 0 1 0 1 0 1 0 0
 1 1 1 1 1 1 0 1 0 0 1]
```

In [150]:
```
final_submission = pd.DataFrame(data_test_mod['PassengerId'])
```

In [151]:
```
final_submission['Survived'] = pred_final
```

In [152]:
```
final_submission
```

Out[152]:

	PassengerId	Survived
0	892	0
1	893	1
2	894	0
3	895	0
4	896	1
...	...	...
413	1305	0
414	1306	1
415	1307	0
416	1308	0
417	1309	1

418 rows × 2 columns