Asteroid Hazard prediction using classification models

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
df=pd.read_csv('dataset.csv')
```

```
C:\Users\KIIT\AppData\Local\Temp\ipykernel_7756\1378625307.py:1: DtypeWarning: Columns (3,4,5) have mixed types. Specify dtype option on import or set low_memory=False.
  df=pd.read_csv('dataset.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	id	spkid	full_name	pdes	name	prefix	neo	pha	H	diameter	...	sigma_i
0	a0000001	2000001	1 Ceres	1	Ceres	NaN	N	N	3.40	939.400	...	4.608900e-09
1	a0000002	2000002	2 Pallas	2	Pallas	NaN	N	N	4.20	545.000	...	3.469400e-06
2	a0000003	2000003	3 Juno	3	Juno	NaN	N	N	5.33	246.596	...	3.223100e-06
3	a0000004	2000004	4 Vesta	4	Vesta	NaN	N	N	3.00	525.400	...	2.170600e-07
4	a0000005	2000005	5 Astraea	5	Astraea	NaN	N	N	6.90	106.699	...	2.740800e-06

5 rows × 45 columns

In [4]:
```
df.shape
```

Out[4]:
```
(958524, 45)
```

In [5]:
```
df['pha'].unique()
```

Out[5]:
```
array(['N', 'Y', nan], dtype=object)
```

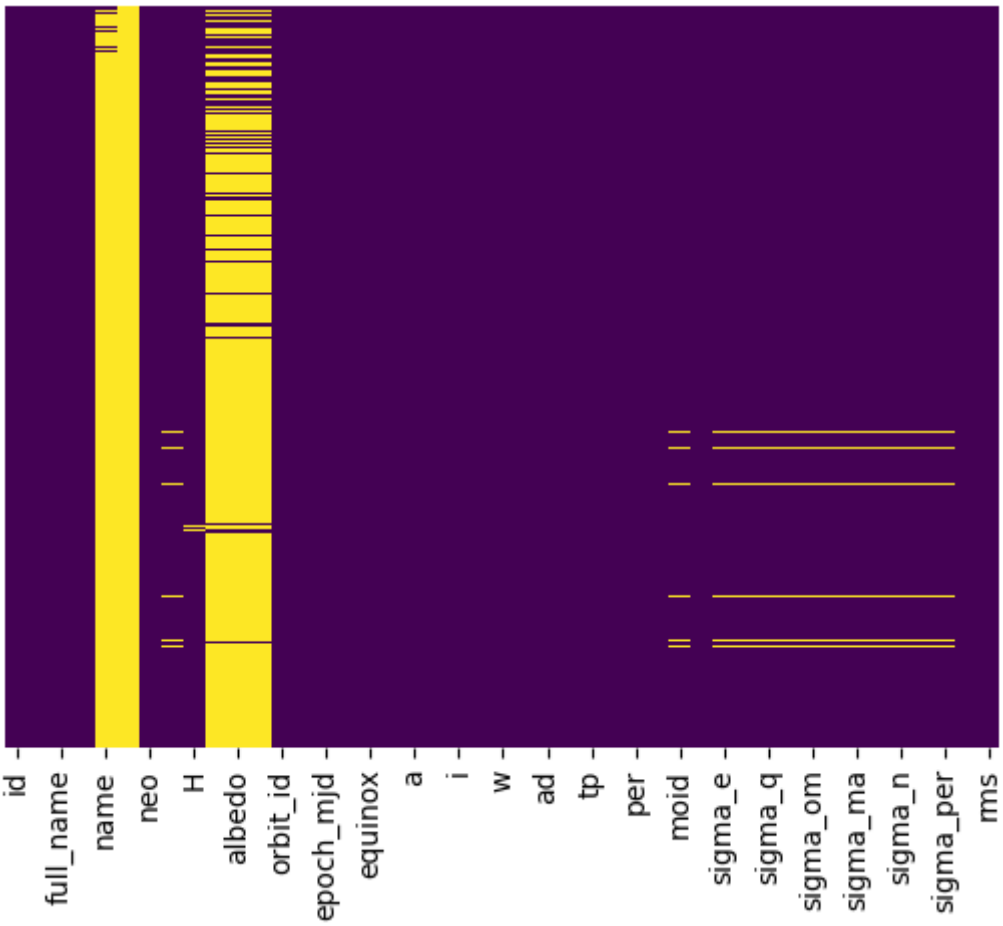
Data Preprocessing(EDA)

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
id                   0
spkid                0
full_name            0
pdes                 0
name            936460
prefix          958506
neo                  4
pha                19921
H                   6263
diameter          822315
albedo            823421
diameter_sigma    822443
orbit_id             0
epoch                0
epoch_mjd            0
epoch_cal            0
equinox              0
e                    0
a                    0
q                    0
i                    0
om                   0
w                    0
ma                   1
ad                   4
n                    0
tp                   0
tp_cal               0
per                  4
per_y                1
moid             19921
moid_ld            127
sigma_e          19922
sigma_a          19922
sigma_q          19922
sigma_i          19922
sigma_om         19922
sigma_w          19922
sigma_ma         19922
sigma_ad         19926
sigma_n          19922
sigma_tp         19922
sigma_per        19926
class                0
rms                  2
dtype: int64
```

In [7]:
```
#plotting null values
sb.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

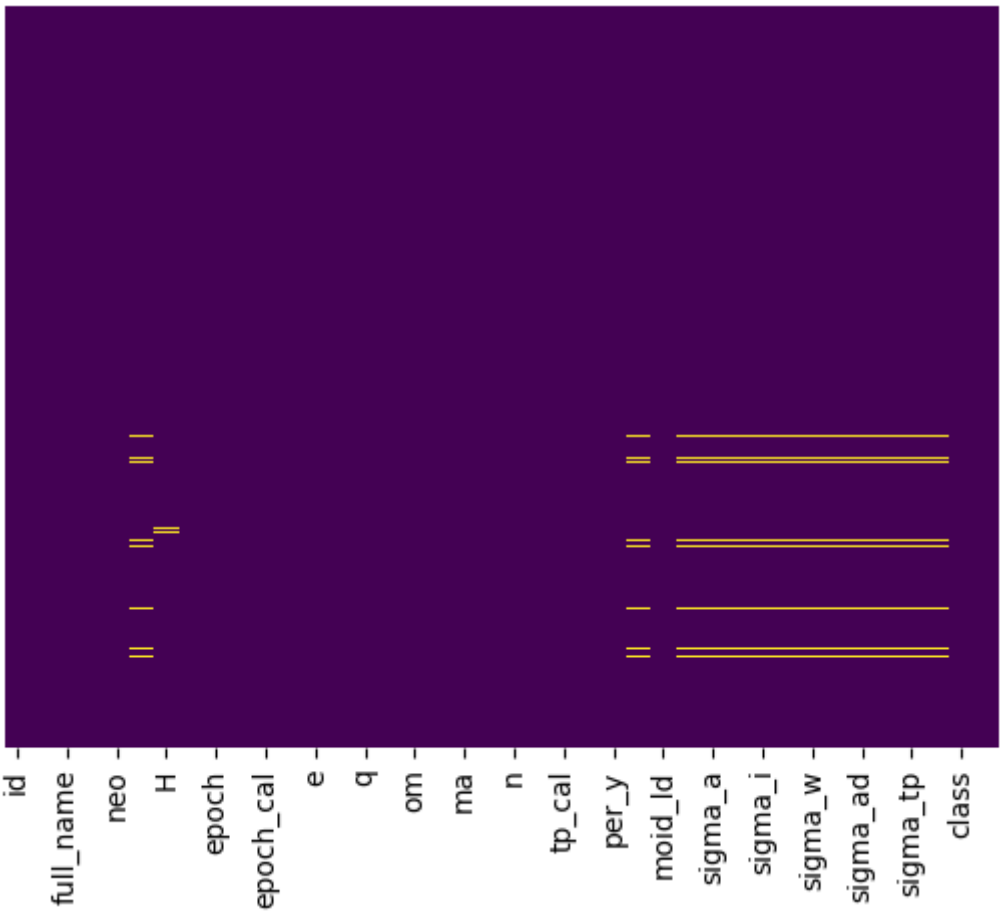
Out[7]:
```
<AxesSubplot:>
```



In [8]:
```
df.drop(['name','prefix','diameter','albedo','diameter_sigma'],axis=1,inplace=True
```

In [9]:
```
sb.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[9]:
```
<AxesSubplot:>
```



In [10]:
```
from sklearn.preprocessing import LabelEncoder
le= LabelEncoder()
```

In [11]:
```
#encoding object(str) dtype to int dtype
df['id']=le.fit_transform(df['id'])
df['full_name']=le.fit_transform(df['full_name'])
df['neo']=le.fit_transform(df['neo'])
df['pha']=le.fit_transform(df['pha'])
df['orbit_id']=le.fit_transform(df['orbit_id'])
df['equinox']=le.fit_transform(df['equinox'])
df['class']=le.fit_transform(df['class'])

#1st converting into str dtype, then to int dtype
df['pdes']=df['pdes'].astype(str)
df['pdes']=le.fit_transform(df['pdes'])
```

In [12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 958524 entries, 0 to 958523
Data columns (total 40 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   id         958524 non-null  int32  
 1   spkid      958524 non-null  int64  
 2   full_name  958524 non-null  int32  
 3   pdes       958524 non-null  int32  
 4   neo        958524 non-null  int32  
 5   pha        958524 non-null  int32  
 6   H          952261 non-null  float64
 7   orbit_id   958524 non-null  int32  
 8   epoch      958524 non-null  float64
 9   epoch_mjd  958524 non-null  int64  
 10  epoch_cal  958524 non-null  float64
 11  equinox    958524 non-null  int32  
 12  e          958524 non-null  float64
 13  a          958524 non-null  float64
 14  q          958524 non-null  float64
 15  i          958524 non-null  float64
 16  om         958524 non-null  float64
 17  w          958524 non-null  float64
 18  ma         958523 non-null  float64
 19  ad         958520 non-null  float64
 20  n          958524 non-null  float64
 21  tp         958524 non-null  float64
 22  tp_cal     958524 non-null  float64
 23  per        958520 non-null  float64
 24  per_y      958523 non-null  float64
 25  moid       938603 non-null  float64
 26  moid_ld    958397 non-null  float64
 27  sigma_e    938602 non-null  float64
 28  sigma_a    938602 non-null  float64
 29  sigma_q    938602 non-null  float64
 30  sigma_i    938602 non-null  float64
 31  sigma_om   938602 non-null  float64
 32  sigma_w    938602 non-null  float64
 33  sigma_ma   938602 non-null  float64
 34  sigma_ad   938598 non-null  float64
 35  sigma_n    938602 non-null  float64
 36  sigma_tp   938602 non-null  float64
 37  sigma_per  938598 non-null  float64
 38  class      958524 non-null  int32  
 39  rms        958522 non-null  float64
dtypes: float64(30), int32(8), int64(2)
memory usage: 263.3 MB
```

In [13]:

```
#encoding null values of float dtype
df['H']=le.fit_transform(df['H'])
df['epoch']=le.fit_transform(df['epoch'])
df['epoch_cal']=le.fit_transform(df['epoch_cal'])
df['e']=le.fit_transform(df['e'])
df['a']=le.fit_transform(df['a'])
df['q']=le.fit_transform(df['q'])
df['i']=le.fit_transform(df['i'])
df['om']=le.fit_transform(df['om'])
df['w']=le.fit_transform(df['w'])
df['ma']=le.fit_transform(df['ma'])
df['ad']=le.fit_transform(df['ad'])
df['n']=le.fit_transform(df['n'])
df['tp']=le.fit_transform(df['tp'])
df['tp_cal']=le.fit_transform(df['tp_cal'])
df['per']=le.fit_transform(df['per'])
```

```
df['per_y']=le.fit_transform(df['per_y'])
df['moid']=le.fit_transform(df['moid'])
df['moid_ld']=le.fit_transform(df['moid_ld'])
df['sigma_e']=le.fit_transform(df['sigma_e'])
df['sigma_a']=le.fit_transform(df['sigma_a'])
df['sigma_q']=le.fit_transform(df['sigma_q'])
df['sigma_i']=le.fit_transform(df['sigma_i'])
df['sigma_om']=le.fit_transform(df['sigma_om'])
df['sigma_w']=le.fit_transform(df['sigma_w'])
df['sigma_ma']=le.fit_transform(df['sigma_ma'])
df['sigma_ad']=le.fit_transform(df['sigma_ad'])
df['sigma_n']=le.fit_transform(df['sigma_n'])
df['sigma_tp']=le.fit_transform(df['sigma_tp'])
df['sigma_per']=le.fit_transform(df['sigma_per'])
df['rms']=le.fit_transform(df['rms'])
```

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
id           0
spkid        0
full_name    0
pdes         0
neo          0
pha          0
H            0
orbit_id     0
epoch        0
epoch_mjd    0
epoch_cal    0
equinox      0
e            0
a            0
q            0
i            0
om           0
w            0
ma           0
ad           0
n            0
tp           0
tp_cal       0
per          0
per_y        0
moid         0
moid_ld      0
sigma_e      0
sigma_a      0
sigma_q      0
sigma_i      0
sigma_om     0
sigma_w      0
sigma_ma     0
sigma_ad     0
sigma_n      0
sigma_tp     0
sigma_per    0
class        0
rms          0
dtype: int64
```

In [15]:
```
#converting float dtype into int dtype
df['H']=df['H'].astype(int)
df['epoch']=df['epoch'].astype(int)
df['epoch_cal']=df['epoch_cal'].astype(int)
```

```
df['e']=df['e'].astype(int)
df['a']=df['a'].astype(int)
df['q']=df['q'].astype(int)
df['i']=df['i'].astype(int)
df['om']=df['om'].astype(int)
df['w']=df['w'].astype(int)
df['ma']=df['ma'].astype(int)
df['ad']=df['ad'].astype(int)
df['n']=df['n'].astype(int)
df['tp']=df['tp'].astype(int)
df['tp_cal']=df['tp_cal'].astype(int)
df['per']=df['per'].astype(int)
df['per_y']=df['per_y'].astype(int)
df['moid']=df['moid'].astype(int)
df['moid_ld']=df['moid_ld'].astype(int)
df['sigma_e']=df['sigma_e'].astype(int)
df['sigma_a']=df['sigma_a'].astype(int)
df['sigma_q']=df['sigma_q'].astype(int)
df['sigma_i']=df['sigma_i'].astype(int)
df['sigma_om']=df['sigma_om'].astype(int)
df['sigma_w']=df['sigma_w'].astype(int)
df['sigma_ma']=df['sigma_ma'].astype(int)
df['sigma_ad']=df['sigma_ad'].astype(int)
df['sigma_n']=df['sigma_n'].astype(int)
df['sigma_tp']=df['sigma_tp'].astype(int)
df['sigma_per']=df['sigma_per'].astype(int)
df['rms']=df['rms'].astype(int)
```

In [16]:
```
df.head()
```

Out[16]:

	id	spkid	full_name	pdes	neo	pha	H	orbit_id	epoch	epoch_mjd	...	sigma_i	sigm
0	0	2000001	413389	0	0	0	11	517	4925	58600	...	0	
1	1	2000002	413390	113927	0	0	18	494	5245	59000	...	3517	
2	2	2000003	413391	635604	0	0	32	323	5245	59000	...	1567	
3	3	2000004	413392	746715	0	0	8	489	4925	58600	...	5	
4	4	2000005	413393	857830	0	0	189	325	5245	59000	...	223	

5 rows × 40 columns

In [17]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix
```

In [18]:
```
#independent and dependent var
x=df.drop(labels=['pha'],axis=1)
y=df['pha']
```

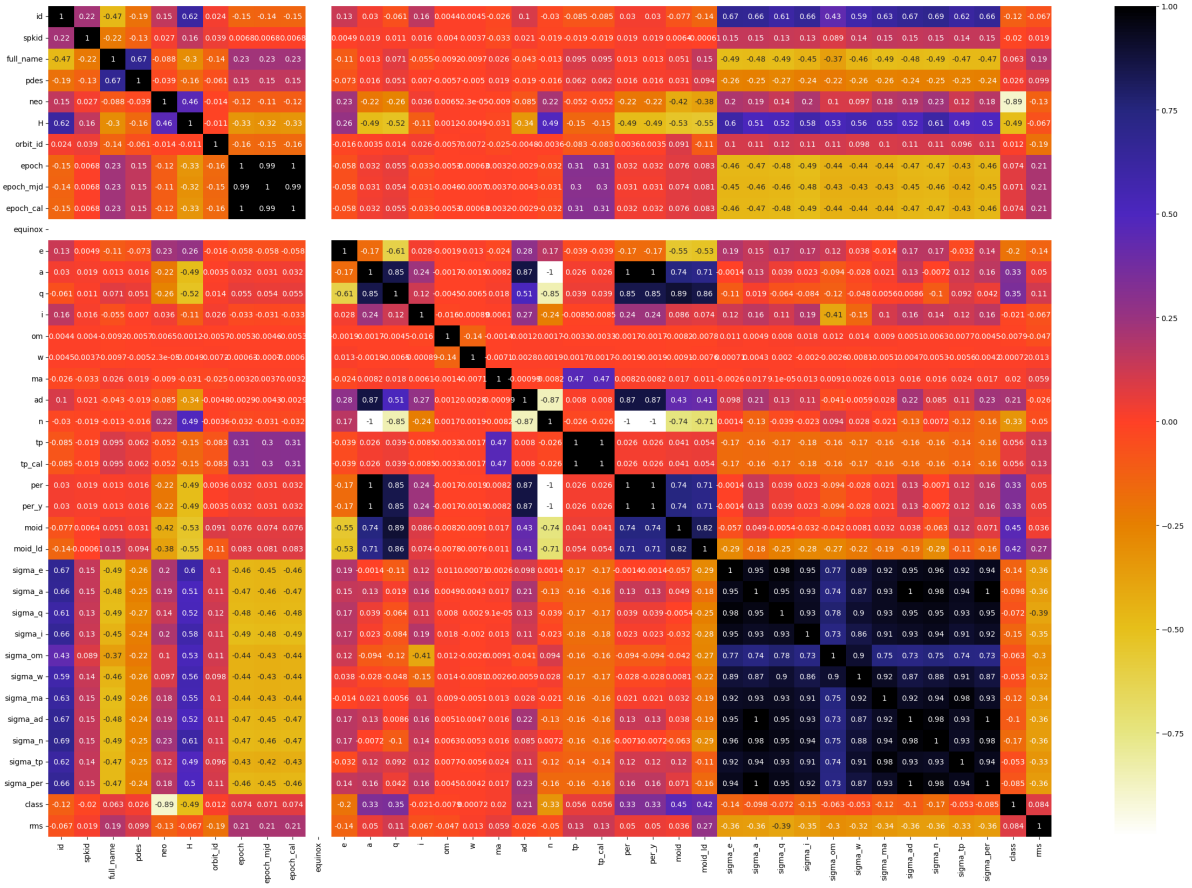
In [19]:
```
#No=0, Yes=1, Nan=2
y.unique()
```

Out[19]:
```
array([0, 1, 2])
```

In [20]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3,random_state
x_train.shape,x_test.shape
```

Out[20]:
```
((670966, 39), (287558, 39))
```

In [21]:
```
#pearson correlation
plt.figure(figsize=(30,20))
cor= x_train.corr()
sb.heatmap(cor,annot=True,cmap=plt.cm.CMRmap_r)
plt.show()
```



In [22]:
```
def correlation(df, thresold):
    col_corr=set()
    corr_matrix=df.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(1):
            if abs(corr_matrix.iloc[i, j]) > thresold:
                colname=corr_matrix.columns[i]
                col_corr.add(colname)
    return col_corr
```

In [23]:
```
#columns with correlation > 0.7
corr_features=correlation(x_train, 0.7)
len(set(corr_features))
```

Out[23]:
```
1
```

In [24]:
```
corr_features
```

Out[24]:
```
{'id'}
```

In [25]:
```
#removing columns with correlation greater than 0.7
x_train.drop(corr_features,axis=1)
x_test.drop(corr_features,axis=1)
```

Out[25]:

	spkid	full_name	pdes	neo	H	orbit_id	epoch	epoch_mjd	epoch_cal	equinox
840267	3722235	294432	407212	0	6042	185	5245	59000	5245	0
493247	2493248	906636	850330	0	2657	445	5245	59000	5245	0
93180	2093181	506569	950950	0	2287	374	5245	59000	5245	0
553332	3203861	8703	119928	0	5655	33	5245	59000	5245	0
113153	2113154	526542	14619	0	2239	401	5245	59000	5245	0
...	...	...	...	...	...	...	...	...	...	...
501547	2501548	914936	859553	0	3755	1	5245	59000	5245	0
244662	2244663	658051	574120	0	3255	33	5245	59000	5245	0
779931	3809038	234175	346844	0	4255	0	5245	59000	5245	0
517855	2517856	931244	877672	0	3555	54	5245	59000	5245	0
670050	3528554	123973	236198	0	9489	575	2259	55241	2259	0

287558 rows × 38 columns

In [26]:
```
from sklearn import preprocessing
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import mutual_info_classif
from sklearn.tree import DecisionTreeClassifier
```

In [27]:
```
#Feature selection
mutual_info = mutual_info_classif(x_train, y_train)
mutual_info
```

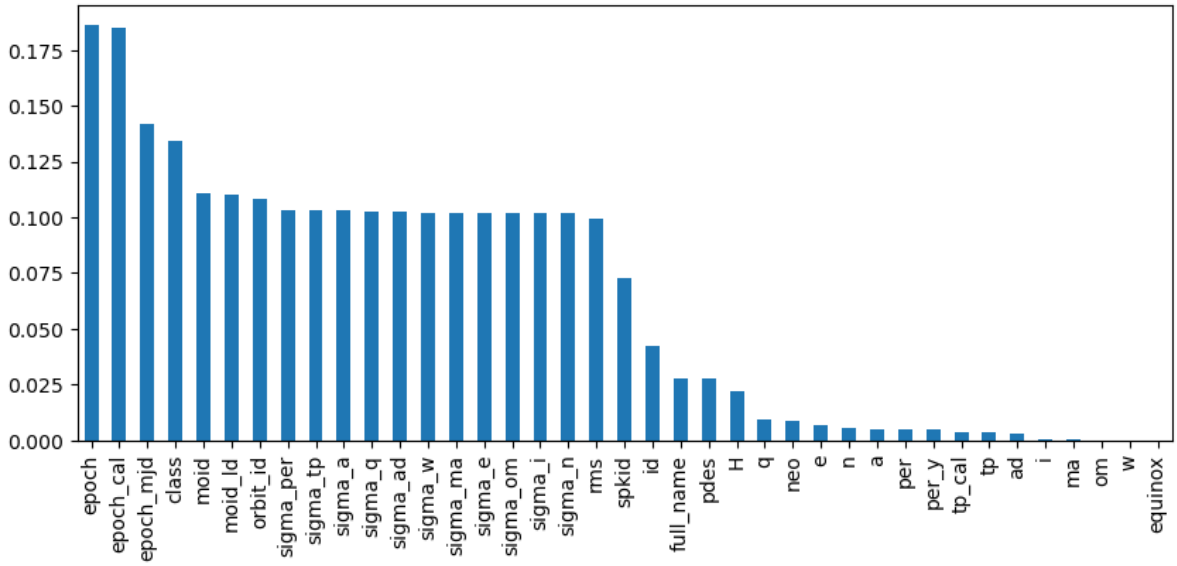
Out[27]:
```
array([4.23157382e-02, 7.26500991e-02, 2.76885815e-02, 2.74884438e-02,
       8.77294079e-03, 2.17851932e-02, 1.07965429e-01, 1.86033103e-01,
       1.42068765e-01, 1.85282728e-01, 0.00000000e+00, 6.56521805e-03,
       5.16283497e-03, 9.52389898e-03, 5.19180817e-04, 4.54385172e-05,
       0.00000000e+00, 3.00639235e-04, 2.99461452e-03, 5.17145133e-03,
       3.69822209e-03, 3.72211701e-03, 5.15845444e-03, 5.14232958e-03,
       1.10550657e-01, 1.10373600e-01, 1.01920176e-01, 1.03059307e-01,
       1.02740930e-01, 1.01690091e-01, 1.01901924e-01, 1.02023535e-01,
       1.01968328e-01, 1.02644065e-01, 1.01596484e-01, 1.03285560e-01,
       1.03320965e-01, 1.34096844e-01, 9.95199841e-02])
```

In [28]:
```
mutual_info=pd.Series(mutual_info)
mutual_info.index=x_train.columns
mutual_info.sort_values(ascending=False)
```

Out[28]:
```
epoch        0.186033
epoch_cal    0.185283
epoch_mjd    0.142069
class        0.134097
moid         0.110551
moid_ld      0.110374
orbit_id     0.107965
sigma_per    0.103321
sigma_tp     0.103286
sigma_a      0.103059
sigma_q      0.102741
sigma_ad     0.102644
sigma_w      0.102024
sigma_ma     0.101968
sigma_e      0.101920
sigma_om     0.101902
sigma_i      0.101690
sigma_n      0.101596
rms          0.099520
spkid        0.072650
id           0.042316
full_name    0.027689
pdes         0.027488
H            0.021785
q            0.009524
neo          0.008773
e            0.006565
n            0.005171
a            0.005163
per          0.005158
per_y        0.005142
tp_cal       0.003722
tp           0.003698
ad           0.002995
i            0.000519
ma           0.000301
om           0.000045
w            0.000000
equinox      0.000000
dtype: float64
```

In [29]:
```
#columns with high mutual_info
mutual_info.sort_values(ascending=False).plot.bar(figsize=(10,4))
```

Out[29]:
```
<AxesSubplot:>
```



In [30]:
```
#selecting 23 best columns in respect to mutual_info
cols=SelectKBest(mutual_info_classif,k=23)
cols.fit(x_train.fillna(0),y_train)
x_train.columns[cols.get_support()]
```

Out[30]:
```
Index(['id', 'spkid', 'full_name', 'pdes', 'orbit_id', 'epoch', 'epoch_mjd',
       'epoch_cal', 'moid', 'moid_ld', 'sigma_e', 'sigma_a', 'sigma_q',
       'sigma_i', 'sigma_om', 'sigma_w', 'sigma_ma', 'sigma_ad', 'sigma_n',
       'sigma_tp', 'sigma_per', 'class', 'rms'],
      dtype='object')
```

Model Training

In [31]:
```
#DecisionTreeClassifier(acc~99.99)
model=DecisionTreeClassifier()
model.fit(x_train,y_train)
```

Out[31]:
```
DecisionTreeClassifier()
```

In [32]:
```
x_train_accuracy=model.predict(x_train)
train_accuracy=accuracy_score(x_train_accuracy,y_train)
train_accuracy
```

Out[32]:
```
1.0
```

In [33]:
```
x_test_accuracy=model.predict(x_test)
test_accuracy=accuracy_score(x_test_accuracy,y_test)
test_accuracy
```

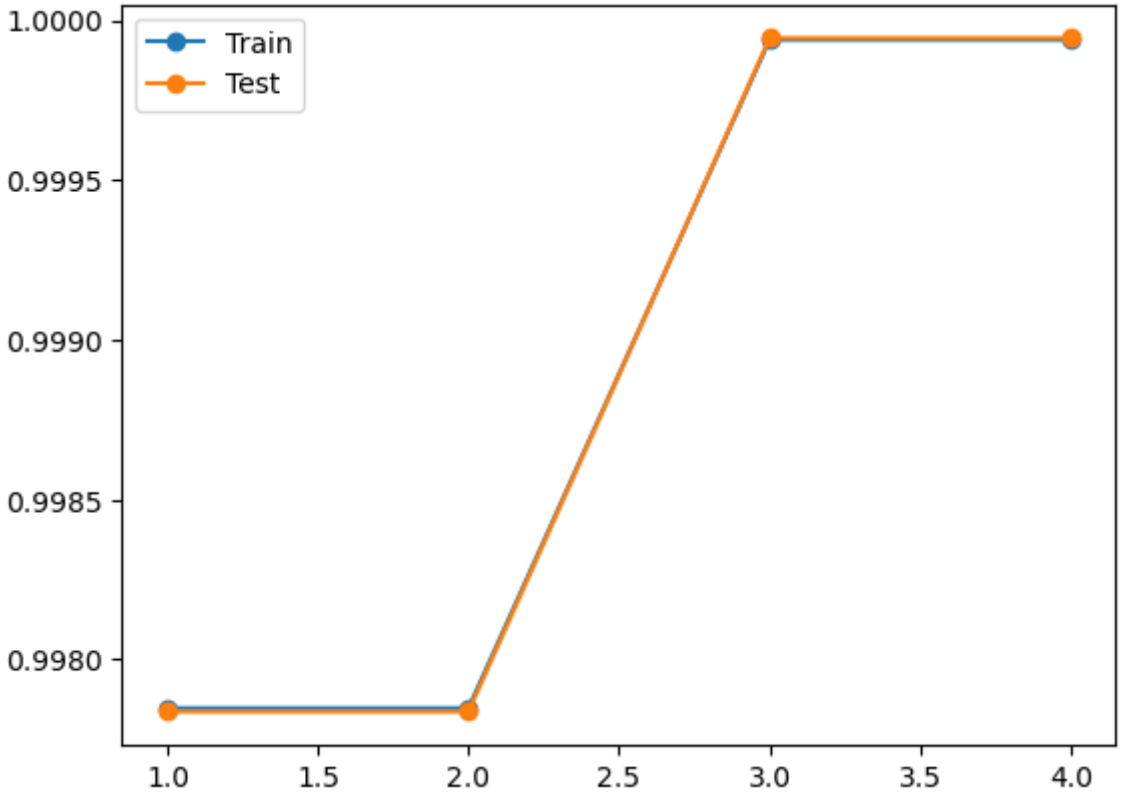
Out[33]:
```
0.9999304488138046
```

In [34]:
```
#checking overfit
train_scores, test_scores = list(), list()
values = [i for i in range(1, 5)]

for i in values:
 model = DecisionTreeClassifier(max_depth=i)
 model.fit(x_train, y_train)
 train_yhat = model.predict(x_train)
 train_acc = accuracy_score(y_train, train_yhat)
 train_scores.append(train_acc)
 test_yhat = model.predict(x_test)
 test_acc = accuracy_score(y_test, test_yhat)
 test_scores.append(test_acc)
 print('>%d, train: %.3f, test: %.3f' % (i, train_acc, test_acc))

plt.plot(values, train_scores, '-o', label='Train')
plt.plot(values, test_scores, '-o', label='Test')
plt.legend()
plt.show()
```

```
>1, train: 0.998, test: 0.998
>2, train: 0.998, test: 0.998
>3, train: 1.000, test: 1.000
>4, train: 1.000, test: 1.000
```



In [35]:
```
#SVM(acc~99.85)
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.datasets import make_classification
from sklearn import svm
```

In [36]:
```
sc = StandardScaler()
sc.fit(x_train)
x_train_svm = sc.transform(x_train)
x_test_svm = sc.transform(x_test)

model= SVC(kernel='linear',random_state=0,C=1.0)
model.fit(x_train_svm,y_train)
```

Out[36]:
```
SVC(kernel='linear', random_state=0)
```

In [37]:
```
pred1 = model.predict(x_train_svm)
pred2 = model.predict(x_test_svm)
```

In [38]:
```
train_svm=accuracy_score(y_train,pred1)
test_svm=accuracy_score(y_test,pred2)
print(train_svm)
print(test_svm)
```

```
0.9986303329825953
0.9985915884795415
```

In [39]:
```
#RandomForestClassifier(acc~99.78)
from sklearn.ensemble import RandomForestClassifier
classifier=RandomForestClassifier(n_estimators=20,criterion='gini',random_state=1,r
classifier.fit(x_train,y_train)
```

Out[39]:
```
RandomForestClassifier(max_depth=3, n_estimators=20, random_state=1)
```

In [40]:
```
rf_pred=classifier.predict(x_test)
test_ranF=accuracy_score(y_test,rf_pred)
```

```
print(test_ranF)
```

```
0.9978369581093206
```

In [41]:
```
#NaiveBayes(acc~98.12)
from sklearn.naive_bayes import GaussianNB
classifier=GaussianNB()
classifier.fit(x_train,y_train)
```

Out[41]:
```
GaussianNB()
```

In [42]:
```
nb_pred=classifier.predict(x_test)
test_nb=accuracy_score(y_test,nb_pred)
print(test_nb)
```

```
0.9812211797272202
```

In [43]:
```
#Logistic_Regression(acc~99.76)
from sklearn.linear_model import LogisticRegression
regression = LogisticRegression(random_state=0)
regression.fit(x_train,y_train)
```

```
C:\Anaconda\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWa
rning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[43]:
```
LogisticRegression(random_state=0)
```

In [44]:
```
log_pred=regression.predict(x_test)
test_log=accuracy_score(y_test,log_pred)
print(test_log)
```

```
0.9976943781776199
```

In [45]:
```
#XGBoostClassifier(acc~98.12)
import xgboost
from xgboost import XGBClassifier
```

In [46]:
```
xg_model=XGBClassifier()
xg_model.fit(x_train,y_train)
```

Out[46]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              objective='multi:softprob', predictor=None, ...)
```

In [47]:
```
xg_pred=classifier.predict(x_test)
test_xg=accuracy_score(y_test,xg_pred)
print(test_xg)
```

```
0.9812211797272202
```

In [48]:
```
#KNN(acc~98.12)
from sklearn.neighbors import KNeighborsClassifier
```

In [49]:
```
knn_model=KNeighborsClassifier()
knn_model.fit(x_train,y_train)
```

Out[49]:
```
KNeighborsClassifier()
```

In [50]:
```
knn_pred=classifier.predict(x_test)
test_knn=accuracy_score(y_test,knn_pred)
print(test_knn)
```

```
0.9812211797272202
```

Accuracy in different classification models

In [52]:
```
print('KNN- ',test_knn)
print('DecisionTreeClassfier- ',test_accuracy)
print('SupportVectorMachine- ',test_svm)
print('RandomForestClassifier- ',test_ranF)
print('NaiveBayes- ',test_nb)
print('LogisticRegression- ',test_log)
print('XGBoost- ',test_xg)
```

```
KNN-  0.9812211797272202
DecisionTreeClassfier-  0.9999304488138046
SupportVectorMachine-  0.9985915884795415
RandomForestClassifier-  0.9978369581093206
NaiveBayes-  0.9812211797272202
LogisticRegression-  0.9976943781776199
XGBoost-  0.9812211797272202
```

Model Building

In [56]:
```
dt_model=DecisionTreeClassifier()
dt_model.fit(x_train,y_train)
```

Out[56]:
```
DecisionTreeClassifier()
```

In [57]:
```
train_acc=model.predict(x_train)
train_dt=accuracy_score(train_acc,y_train)
train_dt
```

Out[57]:
```
1.0
```

In [62]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,test_acc))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    280858
           1       0.98      0.98      0.98       622
           2       1.00      1.00      1.00      6078

    accuracy                           1.00    287558
   macro avg       0.99      0.99      0.99    287558
weighted avg       1.00      1.00      1.00    287558
```

In [63]:
```
test_acc=model.predict(x_test)
test_dt=accuracy_score(test_acc,y_test)
print('Accuracy score is ', test_dt)
```

```
Accuracy score is  0.9999269712544947
```