Problem Statement: To Predict How Best the Datafits and To predict the BreastCancer based on the given Features

KMeans Clustering

1)Data collection

In [2]: df=pd.read_csv(r"C:\Users\Jayadeep\Downloads\BreastCancerPrediction.csv")
df

Out[2]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	poin
0	842302	М	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	
1	842517	М	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	
2	84300903	М	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	
3	84348301	М	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	
4	84358402	М	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	
564	926424	М	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	
565	926682	М	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	
566	926954	М	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	
567	927241	М	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	
568	92751	В	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	

569 rows × 33 columns

2)Data cleaning and preprocessing

In [3]:	df	.head()									
Out[3]:		id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	co points
	0	842302	М	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0
	1	842517	М	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0
	2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0
	3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0
	4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0
	5 ro	ws × 33 c	olumns								
	4										•
In [4]:	طد .	+ail()									
111 [4].	uı.	call()									
Out[4]:		id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	co points_
Out[4]:	564	id 926424	diagnosis M	radius_mean 21.56	texture_mean 22.39	perimeter_mean 142.00	area_mean 1479.0	smoothness_mean 0.11100	compactness_mean 0.11590	concavity_mean 0.24390	
Out[4]:										-	points_
Out[4]:	565	926424	М	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	points ₀
Out[4]:	565	926424 926682 926954	M M	21.56 20.13	22.39 28.25	142.00 131.20	1479.0 1261.0	0.11100 0.09780	0.11590 0.10340	0.24390 0.14400	0 0
Out[4]:	565 566	926424 926682 926954 927241	M M M	21.56 20.13 16.60	22.39 28.25 28.08	142.00 131.20 108.30	1479.0 1261.0 858.1	0.11100 0.09780 0.08455	0.11590 0.10340 0.10230	0.24390 0.14400 0.09251	0 0 0
Out[4]:	565 566 567 568	926424 926682 926954 927241	M M M M	21.56 20.13 16.60 20.60	22.39 28.25 28.08 29.33	142.00 131.20 108.30 140.10	1479.0 1261.0 858.1 1265.0	0.11100 0.09780 0.08455 0.11780	0.11590 0.10340 0.10230 0.27700	0.24390 0.14400 0.09251 0.35140	0 0 0 0
Out[4]:	565 566 567 568	926424 926682 926954 927241 92751	M M M M	21.56 20.13 16.60 20.60	22.39 28.25 28.08 29.33	142.00 131.20 108.30 140.10	1479.0 1261.0 858.1 1265.0	0.11100 0.09780 0.08455 0.11780	0.11590 0.10340 0.10230 0.27700	0.24390 0.14400 0.09251 0.35140	0 0 0 0
Out[4]: In [5]:	565 566 567 568 5 ro	926424 926682 926954 927241 92751	M M M M	21.56 20.13 16.60 20.60	22.39 28.25 28.08 29.33	142.00 131.20 108.30 140.10	1479.0 1261.0 858.1 1265.0	0.11100 0.09780 0.08455 0.11780	0.11590 0.10340 0.10230 0.27700	0.24390 0.14400 0.09251 0.35140	points_

In [6]: df.describe

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Out[6]: <bound method NDFrame.describe of</pre>
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```

1	0.18660	0.2416	0.1860	0.2750
2	0.42450	0.4504	0.2430	0.3613
3	0.86630	0.6869	0.2575	0.6638
4	0.20500	0.4000	0.1625	0.2364
• •	• • •	• • •	•••	• • •
564	0.21130	0.4107	0.2216	0.2060
565	0.19220	0.3215	0.1628	0.2572
566	0.30940	0.3403	0.1418	0.2218
567	0.86810	0.9387	0.2650	0.4087
568	0.06444	0.0000	0.0000	0.2871

fractal_dimension_worst Unnamed: 32 0 0.11890 NaN 0.08902 NaN 1 0.08758 2 NaN 3 0.17300 NaN 0.07678 NaN 4 564 0.07115 NaN 565 0.06637 NaN 0.07820 566 NaN 567 0.12400 NaN 568 0.07039 NaN

[569 rows x 33 columns]>

In [7]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):

#	Column	Non-Null Count	Dtype
0	id	569 non-null	 int64
1	diagnosis	569 non-null	object
2	radius_mean	569 non-null	float64
3	texture_mean	569 non-null	float64
4	perimeter_mean	569 non-null	float64
5	area_mean	569 non-null	float64
6	smoothness_mean	569 non-null	float64
7	compactness_mean	569 non-null	float64
8	concavity_mean	569 non-null	float64
9	concave points_mean	569 non-null	float64
10	symmetry_mean	569 non-null	float64
11	fractal_dimension_mean	569 non-null	float64
12	radius_se	569 non-null	float64
13	texture_se	569 non-null	float64
14	perimeter_se	569 non-null	float64
15	area_se	569 non-null	float64
16	smoothness_se	569 non-null	float64
17	compactness_se	569 non-null	float64
18	concavity_se	569 non-null	float64
19	concave points_se	569 non-null	float64
20	symmetry_se	569 non-null	float64
21	<pre>fractal_dimension_se</pre>	569 non-null	float64
22	radius_worst	569 non-null	float64
23	texture_worst	569 non-null	float64
24	perimeter_worst	569 non-null	float64
25	area_worst	569 non-null	float64
26	smoothness_worst	569 non-null	float64
27	compactness_worst	569 non-null	float64
28	concavity_worst	569 non-null	float64
29	concave points_worst	569 non-null	float64
30	symmetry_worst	569 non-null	float64
31	fractal_dimension_worst	569 non-null	float64
32	Unnamed: 32	0 non-null	float64
dtyne	es: float64(31) int64(1)	object(1)	

dtypes: float64(31), int64(1), object(1)

memory usage: 146.8+ KB

In [8]:	<pre>df.isnull().sum()</pre>	
Out[8]:	id	0
	diagnosis	0
	radius_mean	0
	texture_mean	0
	perimeter_mean	0
	area_mean	0
	smoothness_mean	0
	compactness_mean	0
	concavity_mean	0
	concave points_mean	0
	symmetry_mean	0
	<pre>fractal_dimension_mean</pre>	0
	radius_se	0
	texture_se	0
	perimeter_se	0
	area_se	0
	smoothness_se	0
	compactness_se	0
	concavity_se	0
	concave points_se	0
	symmetry_se	0
	<pre>fractal_dimension_se</pre>	0
	radius_worst	0
	texture_worst	0
	perimeter_worst	0
	area_worst	0
	smoothness_worst	0
	compactness_worst	0
	concavity_worst	0
	concave points_worst	0
	symmetry_worst	0
	<pre>fractal_dimension_worst</pre>	0
	Unnamed: 32	569
	dtype: int64	

In [9]: df.drop(['Unnamed: 32'],axis=1)

Out[9]:

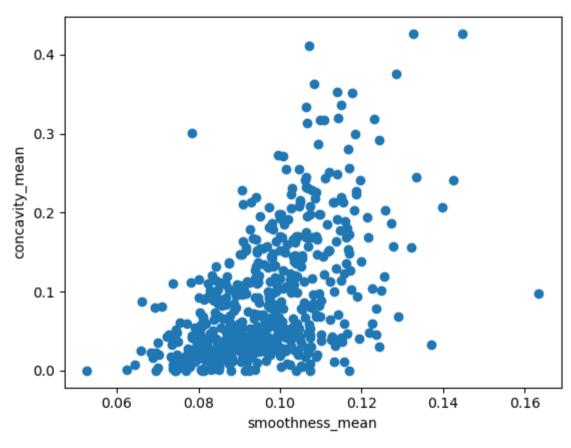
	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	poin
0	842302	М	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	
1	842517	М	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	
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564	926424	М	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	
565	926682	М	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	
566	926954	М	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	
567	927241	М	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	
568	92751	В	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	

569 rows × 32 columns

3)Exploratory data Analysis

```
In [10]: plt.scatter(df["smoothness_mean"],df["concavity_mean"])
    plt.xlabel("smoothness_mean")
    plt.ylabel("concavity_mean")

Out[10]: Text(0, 0.5, 'concavity_mean')
```



4)Training our model

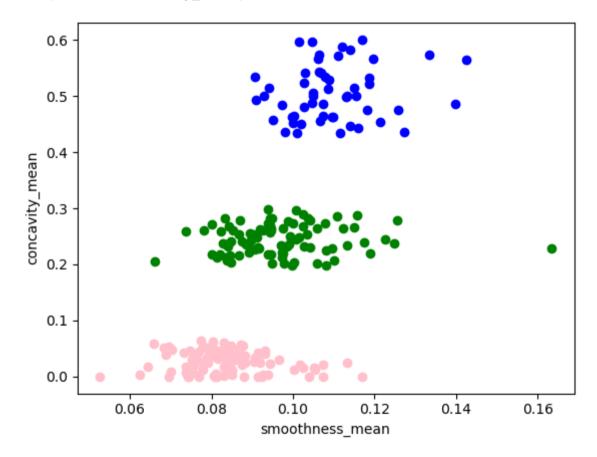
```
In [11]: from sklearn.cluster import KMeans
        km=KMeans()
In [12]:
         km
Out[12]: KMeans()
In [13]: v predicted=km.fit predict(df[["smoothness mean","concavity mean"]])
         v predicted
Out[13]: array([3, 0, 1, 1, 1, 5, 0, 0, 1, 1, 4, 0, 1, 0, 1, 5, 7, 5, 5, 7, 4, 4,
                1, 0, 5, 1, 5, 5, 5, 0, 1, 0, 1, 5, 5, 5, 5, 4, 4, 0, 4, 0, 1, 0,
                7, 1, 2, 0, 7, 4, 2, 2, 2, 5, 7, 4, 5, 5, 2, 4, 2, 4, 1, 7, 0, 5,
                4, 4, 3, 4, 0, 0, 5, 7, 4, 0, 7, 5, 6, 4, 4, 0, 3, 1, 4, 5, 0, 5,
                7, 0, 4, 0, 4, 4, 5, 5, 4, 2, 4, 0, 0, 2, 2, 7, 4, 1, 7, 4, 6, 7,
                4, 0, 3, 7, 4, 4, 0, 5, 1, 7, 4, 5, 6, 0, 7, 2, 7, 0, 0, 1, 4, 5,
                0, 7, 0, 4, 4, 4, 5, 4, 2, 0, 4, 4, 2, 4, 5, 0, 0, 4, 4, 5, 6, 4,
                0, 4, 1, 7, 2, 2, 7, 0, 1, 7, 5, 2, 4, 7, 1, 4, 4, 7, 1, 4, 2, 2,
                5, 5, 2, 2, 3, 1, 7, 7, 7, 2, 7, 4, 4, 4, 1, 4, 2, 0, 5, 4, 5, 0,
                0, 0, 4, 0, 6, 5, 7, 7, 4, 7, 0, 7, 5, 4, 3, 5, 0, 0, 7, 7, 0, 0,
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                0, 7, 2, 4, 3, 4, 4, 4, 2, 4, 7, 7, 0, 4, 4, 4, 4, 7, 4, 4, 4, 5,
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                0, 0, 2, 2, 0, 7, 5, 4, 0, 5, 0, 5, 4, 7, 4, 4, 7, 4, 2, 2, 0, 6,
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                7, 4, 7, 1, 7, 4, 5, 7, 7, 4, 5, 5, 4, 4, 4, 1, 2, 7, 4, 4, 4, 4,
                0, 4, 7, 4, 2, 5, 7, 1, 5, 4, 2, 0, 7, 0, 4, 4, 4, 4, 2, 4, 2, 2,
                2, 4, 2, 4, 7, 7, 2, 2, 0, 0, 4, 2, 1, 3, 1, 5, 0, 6, 2])
```

localhost:8889/notebooks/Mini Project4.ipynb

In [14]: df["cluster"]=y_predicted In [15]: df.head() Out[15]: id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean points 842302 М 17.99 10.38 122.80 1001.0 0.11840 0.27760 0.3001 0 0 842517 132.90 1326.0 20.57 17.77 0.08474 0.07864 0.0869 Μ 0 **2** 84300903 19.69 21.25 130.00 1203.0 0.10960 0.15990 0.1974 0 M **3** 84348301 11.42 20.38 77.58 386.1 0.14250 0.28390 Μ 0.2414 0 **4** 84358402 Μ 20.29 14.34 135.10 1297.0 0.10030 0.13280 0.1980 0 5 rows × 34 columns

```
In [23]: df1=df[df.cluster==0]
    df2=df[df.cluster==1]
    df3=df[df.cluster==2]
    plt.scatter(df1["smoothness_mean"],df1["concavity_mean"],color='green')
    plt.scatter(df2["smoothness_mean"],df2["concavity_mean"],color='blue')
    plt.scatter(df3["smoothness_mean"],df3["concavity_mean"],color='pink')
    plt.xlabel("smoothness_mean")
    plt.ylabel("concavity_mean")
```

Out[23]: Text(0, 0.5, 'concavity_mean')



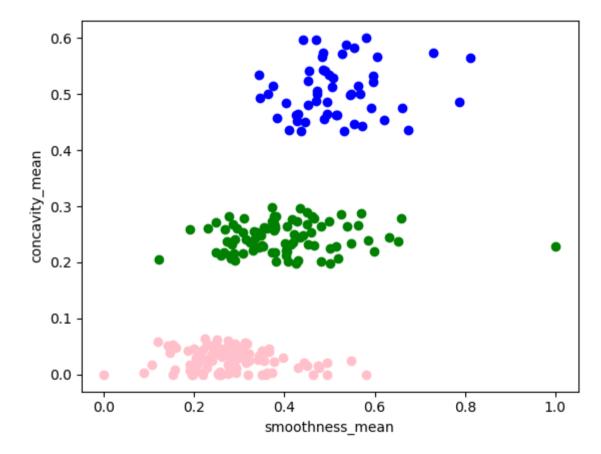
```
from sklearn.preprocessing import MinMaxScaler
In [20]:
           scaler=MinMaxScaler()
           scaler.fit(df[["concavity mean"]])
          df["concavity mean"]=scaler.transform(df[["concavity_mean"]])
          df.head()
Out[20]:
                     id diagnosis radius mean texture mean perimeter mean area mean smoothness mean compactness mean concavity mean
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            3 84348301
                                                                                                                                   0.565604
              84358402
                               М
                                         20.29
                                                       14.34
                                                                     135.10
                                                                                1297.0
                                                                                                 0.10030
                                                                                                                     0.13280
                                                                                                                                   0.463918
                                                                                                                                                 0
           5 rows × 34 columns
In [24]:
          scaler=MinMaxScaler()
           scaler.fit(df[["smoothness mean"]])
          df["smoothness mean"]=scaler.transform(df[["smoothness_mean"]])
          df.head()
Out[24]:
                     id diagnosis radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean
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                                                                     122.80
                                                                                1001.0
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                                                       17.77
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                                                                     130.00
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                                                                                                                                                 0
                               М
                                         20.29
                                                       14.34
                                                                     135.10
                                                                                1297.0
                                                                                                 0.430351
                                                                                                                     0.13280
                                                                                                                                   0.463918
                                                                                                                                                 0
            4 84358402
           5 rows × 34 columns
```

```
In [25]: km=KMeans()
In [26]: y predicted=km.fit predict(df[["smoothness mean","concavity mean"]])
         v predicted
Out[26]: array([2, 3, 7, 5, 7, 5, 3, 4, 5, 7, 6, 3, 7, 3, 7, 5, 3, 5, 0, 3, 4, 4,
                7, 3, 5, 7, 0, 0, 0, 3, 7, 0, 7, 0, 0, 0, 0, 1, 1, 0, 6, 5, 7, 0,
                3, 7, 1, 5, 4, 1, 1, 6, 6, 5, 1, 1, 0, 5, 6, 1, 4, 4, 7, 6, 0, 5,
                4, 6, 2, 1, 3, 3, 0, 4, 1, 3, 4, 0, 2, 4, 4, 0, 2, 5, 1, 0, 3, 0,
                1, 4, 1, 3, 6, 4, 0, 0, 4, 4, 1, 3, 3, 4, 6, 4, 4, 5, 4, 1, 2, 1,
                4, 0, 7, 4, 4, 1, 3, 5, 7, 3, 1, 0, 2, 4, 6, 1, 1, 3, 5, 7, 4, 0,
                0, 3, 3, 1, 4, 1, 5, 4, 1, 3, 4, 1, 6, 4, 0, 3, 3, 6, 4, 0, 2, 1,
                3, 1, 7, 6, 1, 6, 4, 3, 7, 4, 3, 6, 1, 3, 7, 1, 4, 1, 5, 4, 1, 1,
                0, 0, 6, 1, 2, 7, 3, 1, 1, 1, 3, 1, 4, 6, 7, 1, 6, 0, 0, 6, 5, 3,
                3, 0, 1, 3, 2, 5, 3, 3, 4, 3, 3, 6, 0, 1, 2, 0, 3, 0, 3, 6, 0, 3,
                1, 4, 4, 0, 1, 4, 4, 3, 6, 0, 5, 6, 6, 0, 1, 1, 7, 3, 3, 0, 1, 6,
                0, 6, 7, 4, 6, 3, 1, 4, 7, 1, 7, 0, 0, 4, 0, 5, 2, 0, 0, 1, 3, 6,
                3, 0, 3, 6, 1, 4, 6, 1, 7, 1, 1, 4, 1, 3, 6, 1, 7, 6, 0, 7, 3, 6,
                3, 6, 3, 1, 3, 1, 4, 6, 1, 1, 1, 1, 6, 4, 7, 3, 7, 4, 1, 6, 1, 6,
                6, 6, 1, 6, 1, 1, 4, 1, 6, 0, 7, 6, 4, 3, 4, 7, 1, 4, 1, 6, 5, 5,
                0, 3, 4, 6, 6, 5, 1, 3, 4, 7, 3, 3, 4, 0, 4, 1, 6, 1, 1, 4, 6, 2,
                2, 0, 6, 3, 4, 1, 6, 4, 6, 1, 1, 1, 6, 3, 0, 1, 3, 7, 0, 6, 7, 0,
                6, 4, 7, 6, 6, 5, 4, 6, 6, 4, 1, 3, 3, 6, 3, 7, 1, 4, 5, 2, 4, 6,
                4, 3, 6, 1, 2, 1, 6, 1, 1, 4, 1, 6, 0, 1, 1, 4, 6, 3, 6, 1, 4, 5,
                1, 4, 1, 0, 4, 3, 4, 6, 4, 1, 6, 6, 7, 4, 7, 0, 1, 0, 1, 1, 1, 6,
                3, 3, 1, 6, 3, 4, 0, 1, 3, 0, 6, 0, 1, 4, 1, 1, 3, 1, 6, 6, 3, 2,
                6, 1, 6, 3, 3, 6, 7, 5, 1, 1, 6, 6, 4, 1, 1, 6, 4, 7, 1, 6, 4, 4,
                0, 0, 1, 7, 4, 6, 6, 6, 0, 6, 6, 3, 4, 1, 0, 7, 3, 5, 4, 0, 5, 5,
                4, 4, 1, 5, 3, 1, 0, 3, 3, 4, 0, 0, 4, 4, 4, 7, 1, 4, 1, 4, 4, 1,
                5, 4, 4, 4, 1, 0, 1, 7, 0, 4, 6, 3, 4, 3, 6, 1, 1, 1, 1, 1, 1, 6,
                6, 1, 6, 1, 6, 1, 1, 6, 3, 3, 4, 6, 7, 2, 7, 0, 3, 2, 6
```

localhost:8889/notebooks/Mini Project4.ipynb

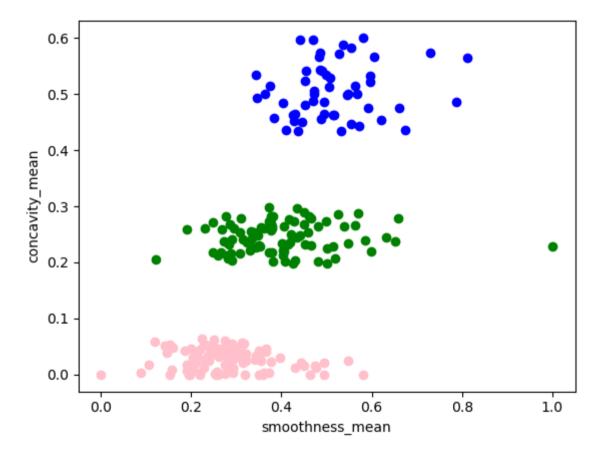
```
In [27]: df1=df[df.cluster==0]
    df2=df[df.cluster==1]
    df3=df[df.cluster==2]
    plt.scatter(df1["smoothness_mean"],df1["concavity_mean"],color='green')
    plt.scatter(df2["smoothness_mean"],df2["concavity_mean"],color='blue')
    plt.scatter(df3["smoothness_mean"],df3["concavity_mean"],color='pink')
    plt.xlabel("smoothness_mean")
    plt.ylabel("concavity_mean")
```

Out[27]: Text(0, 0.5, 'concavity mean')



```
In [29]: df1=df[df.cluster==0]
    df2=df[df.cluster==1]
    df3=df[df.cluster==2]
    plt.scatter(df1["smoothness_mean"],df1["concavity_mean"],color='green')
    plt.scatter(df2["smoothness_mean"],df2["concavity_mean"],color='blue')
    plt.scatter(df3["smoothness_mean"],df3["concavity_mean"],color='pink')
    plt.xlabel("smoothness_mean")
    plt.ylabel("concavity_mean")
```

Out[29]: Text(0, 0.5, 'concavity_mean')



```
In [30]: k_rng=range(1,10)
         sse=[]
In [32]: for k in k rng:
             km=KMeans(n clusters=k)
             km.fit(df[["smoothness_mean","concavity_mean"]])
             sse.append(km.inertia )
         sse
         C:\Users\Jayadeep\anaconda3\lib\site-packages\sklearn\cluster\ kmeans.py:1036: UserWarning: KMeans is known to have
         a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting th
         e environment variable OMP NUM THREADS=3.
           warnings.warn(
Out[32]: [28.97323405387539,
          12.96263525857166,
          9.392190505398347,
          6.936972751219077,
          5.506884287188131,
          4.665441269342259,
          4.065031707454045,
          3.614839704521038,
          3.210208570550766]
```



7

6

sum of squared error

20 -

15

10

5

1

2

3

5

k