sml-assignment-10

October 31, 2024

```
import pandas as pd
     df=pd.read_csv('/content/breast_cancer_survival.csv')
     df
[1]:
          Age Gender
                       Protein1 Protein2 Protein3 Protein4 Tumour_Stage
               FEMALE
                       0.952560
                                  2.15000
                                           0.007972 -0.048340
     1
              FEMALE
                       0.000000
                                  1.38020 -0.498030 -0.507320
                                                                         ΙI
     2
              FEMALE -0.523030
                                                                         ΙI
                                  1.76400 -0.370190
                                                    0.010815
     3
           78
              FEMALE -0.876180
                                  0.12943 -0.370380
                                                     0.132190
                                                                          Ι
     4
           42
              FEMALE 0.226110
                                  1.74910 -0.543970 -0.390210
                                                                         ΙI
     329
               FEMALE
                       0.024598
                                  1.40050
                                           0.024751
                                                     0.280320
                                                                         ΙI
           59
     330
                                                                          Ι
               FEMALE
                       0.100120
                                 -0.46547
                                           0.472370 -0.523870
                                                                         ΙI
     331
              FEMALE
                       0.753820
                                  1.64250 -0.332850
                                                      0.857860
     332
              FEMALE
                       0.972510
                                  1.42680 -0.366570 -0.107820
                                                                         ΙI
     333
           66
              FEMALE
                       0.286380
                                  1.39980 0.318830
                                                     0.836050
                                                                         ΙI
                               Histology ER status PR status HER2 status \
     0
           Infiltrating Ductal Carcinoma Positive Positive
                                                                 Negative
     1
           Infiltrating Ductal Carcinoma Positive
                                                                 Negative
                                                    Positive
     2
           Infiltrating Ductal Carcinoma Positive Positive
                                                                 Negative
     3
           Infiltrating Ductal Carcinoma Positive Positive
                                                                 Negative
     4
           Infiltrating Ductal Carcinoma
                                                                 Positive
                                          Positive Positive
     . .
     329
           Infiltrating Ductal Carcinoma Positive Positive
                                                                 Positive
     330
           Infiltrating Ductal Carcinoma
                                                                 Positive
                                          Positive Positive
     331
           Infiltrating Ductal Carcinoma
                                          Positive
                                                     Positive
                                                                 Negative
     332
          Infiltrating Lobular Carcinoma
                                          Positive
                                                     Positive
                                                                 Negative
     333
           Infiltrating Ductal Carcinoma
                                          Positive
                                                    Positive
                                                                 Negative
                         Surgery_type Date_of_Surgery Date_of_Last_Visit
     0
                                Other
                                             20-May-18
                                                                26-Aug-18
     1
                                Other
                                            26-Apr-18
                                                                25-Jan-19
     2
                           Lumpectomy
                                             24-Aug-18
                                                                08-Apr-20
     3
                                Other
                                                                28-Jul-20
                                             16-Nov-18
     4
                           Lumpectomy
                                             12-Dec-18
                                                                05-Jan-19
```

```
329
                       Lumpectomy
                                        15-Jan-19
                                                            27-Mar-20
330
    Modified Radical Mastectomy
                                        25-Jul-18
                                                            23-Apr-19
331
               Simple Mastectomy
                                        26-Mar-19
                                                             11-0ct-19
332
                       Lumpectomy
                                        26-Nov-18
                                                            05-Dec-18
333
    Modified Radical Mastectomy
                                        04-Feb-19
                                                            10-Aug-19
```

Patient_Status 0 Alive 1 Dead 2 Alive 3 Alive 4 Alive . . 329 Alive 330 Alive 331 Dead 332 Alive 333 Dead

[334 rows x 15 columns]

<ipython-input-2-d66e4b74289f>:1: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
 df['Gender']=df['Gender'].replace(['FEMALE','MALE'],[1,0])
<ipython-input-2-d66e4b74289f>:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
 df['Tumour_Stage']=df['Tumour_Stage'].replace(['I','II','III'],[0,1,2])
<ipython-input-2-d66e4b74289f>:3: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`

```
df['ER status']=df['ER status'].replace(['Positive','Negative'],[1,0])
<ipython-input-2-d66e4b74289f>:4: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set option('future.no silent downcasting', True)`
  df['PR status']=df['PR status'].replace(['Positive','Negative'],[1,0])
<ipython-input-2-d66e4b74289f>:5: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df['HER2 status']=df['HER2 status'].replace(['Positive','Negative'],[1,0])
<ipython-input-2-d66e4b74289f>:6: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df['Patient_Status']=df['Patient_Status'].replace(['Alive','Dead'],[1,0])
<ipython-input-2-d66e4b74289f>:7: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set option('future.no silent downcasting', True)`
  df['Surgery_type']=df['Surgery_type'].replace(['Lumpectomy','Modified Radical
Mastectomy','Simple Mastectomy','Other'],[0,1,2,3])
<ipython-input-2-d66e4b74289f>:8: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  df['Histology']=df['Histology'].replace(['Infiltrating Ductal
Carcinoma', 'Infiltrating Lobular Carcinoma', 'Mucinous Carcinoma'], [0,1,2])
```

[2]:		Age	Gender	r Pro	tein1	Protein2	Protein3	Pro	tein4 7	[umour_	Stage	\
	0	42	:	0.9	52560	2.15000	0.007972	-0.0	48340		1	
	1	54	:	0.0	00000	1.38020	-0.498030	-0.5	07320		1	
	2	63	:	L -0.5	23030	1.76400	-0.370190	0.0	10815		1	
	3	78	:	L -0.8	76180	0.12943	-0.370380	0.1	32190		0	
	4	42	:	0.2	26110	1.74910	-0.543970	-0.3	90210		1	
		•••	•••				•••		•••			
	329	59	:	0.0	24598	1.40050	0.024751	0.2	80320		1	
	330	41	:	0.1	00120	-0.46547	0.472370	-0.5	23870		0	
	331	54	:	0.7	53820	1.64250	-0.332850	0.8	57860		1	
	332	74	:	0.9	72510	1.42680	-0.366570	-0.1	07820		1	
	333	66	;	0.2	86380	1.39980	0.318830	0.8	36050		1	
		Histo	ology	ER st	atus	PR status	HER2 sta	tus	Surgery_	_type	\	
	0		0		1	1		0		3		
	1		0		1	1		0		3		
	2		0		1	1		0		0		
	3		0		1	1		0		3		

	4		0	1	1		1		0		
			•••	•••	•••	•••		•••			
	329		0	1	1		1		0		
	330		0	1	1		1		1		
	331		0	1	1		0		2		
	332		1	1	1		0		0		
	333		0	1	1		0		1		
]	Date_o:	f_Surge	ery Date_of	_Last_Vis	it Patient	t_Sta	itus			
	0		20-May-	•	26-Aug-		_	1.0			
	1	4	26-Apr-	-18	25-Jan-	19		0.0			
	2	:	24-Aug-	-18	08-Apr-	20		1.0			
	3		16-Nov-	-18	28-Jul-	20		1.0			
	4		12-Dec-	-18	05-Jan-	19		1.0			
				•	•••						
	329		15-Jan-		27-Mar-	20		1.0			
	330		25-Jul-		23-Apr-			1.0			
	331		26-Mar-		11-0ct-			0.0			
	332		26-Nov-		05-Dec-			1.0			
	333	(04-Feb-	-19	10-Aug-	19		0.0			
	[334	rows	х 15 сс	olumns]							
F07		/		\							
[3]:	df.f df	illna(0, inpl	Lace=True)							
[3]: [3]:			0, inpl Gender	lace=True) Protein1	Protein2	Protein3	Pro	tein4	Tumour_St	age	\
					Protein2 2.15000				Tumour_St	age 1	\
	df	Age (Gender	Protein1	2.15000		-0.0	48340	Tumour_St	_	\
	0 1 2	Age 42	Gender 1 1	Protein1 0.952560 0.000000 -0.523030	2.15000 1.38020 1.76400	0.007972 -0.498030 -0.370190	-0.0 -0.5	48340	Tumour_St	1	\
	0 1	Age 42 54 63 78	Gender 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180	2.15000 1.38020 1.76400 0.12943	0.007972 -0.498030 -0.370190 -0.370380	-0.0 -0.5 0.0	48340 607320 10815 32190	Tumour_St	1	\
	0 1 2	Age (42 54 63	Gender 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180	2.15000 1.38020 1.76400 0.12943	0.007972 -0.498030 -0.370190	-0.0 -0.5 0.0	48340 607320 10815 32190	Tumour_St	1 1 1	\
	0 1 2 3 4	Age 42 54 63 78 42	Gender 1 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 	2.15000 1.38020 1.76400 0.12943 1.74910 	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 	-0.0 -0.5 0.0 0.1 -0.3	48340 607320 10815 32190 690210 	Tumour_St	1 1 1 0 1	\
	0 1 2 3 4 	Age 42 54 63 78 42 59	Gender 1 1 1 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751	-0.0 -0.5 0.0 0.1 -0.3	48340 607320 10815 32190 90210 	Tumour_St	1 1 1 0 1	\
	0 1 2 3 4 329 330	Age 42 54 63 78 42 59 41	Gender	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370	-0.0 -0.5 0.0 0.1 -0.3	48340 607320 10815 32190 90210 880320 623870	Tumour_St	1 1 1 0 1	\
	0 1 2 3 4 329 330 331	Age 42 54 63 78 42 59 41 54	Gender 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850	-0.0 -0.5 0.0 0.1 -0.3	48340 607320 10815 32190 90210 880320 623870 857860	Tumour_St	1 1 1 0 1	\
	0 1 2 3 4 329 330 331 332	Age 42 54 63 78 42 59 41 54 74	Gender	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8	48340 607320 10815 .32190 80320 280320 257860 .07820	Tumour_St	1 1 1 0 1 1 0 1	\
	0 1 2 3 4 329 330 331	Age 42 54 63 78 42 59 41 54	Gender	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8	48340 607320 10815 .32190 80320 280320 257860 .07820	Tumour_St	1 1 1 0 1	\
	0 1 2 3 4 329 330 331 332	Age 42 54 63 78 42 59 41 54 74 66	Gender 1 1 1 1 1 1 1 1 1 1 1 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510 0.286380	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680 1.39980	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570 0.318830	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8	48340 607320 10815 32190 90210 880320 623870 657860 .07820		1 1 1 0 1 1 0 1	
	0 1 2 3 4 329 330 331 332	Age 42 54 63 78 42 59 41 54 74 66	Gender 1 1 1 1 1 1 1 1 1 1 1 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510 0.286380	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680 1.39980	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8	48340 607320 10815 32190 90210 880320 623870 657860 .07820		1 1 1 0 1 1 0 1	
	0 1 2 3 4 329 330 331 332 333	Age 42 54 63 78 42 59 41 54 74 66	Gender 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510 0.286380 ER status	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680 1.39980 PR status	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570 0.318830	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8 -0.1	48340 607320 10815 32190 90210 880320 623870 657860 .07820	y_type \	1 1 1 0 1 1 0 1	
	0 1 2 3 4 329 330 331 332 333	Age 42 54 63 78 42 59 41 54 74 66	Gender 1 1 1 1 1 1 1 1 1 1 0 0	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510 0.286380 CR status 1	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680 1.39980 PR status	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570 0.318830	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8 -0.1	48340 607320 10815 32190 90210 880320 623870 657860 .07820	y_type \ 3	1 1 1 0 1 1 0 1	
	0 1 2 3 4 329 330 331 332 333	Age 42 54 63 78 42 59 41 54 74 66	Gender 1 1 1 1 1 1 1 1 1 0 0 0	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510 0.286380 ER status 1 1	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680 1.39980 PR status 1	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570 0.318830	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8 -0.1	48340 607320 10815 32190 90210 880320 623870 657860 .07820	y_type \ 3 3	1 1 1 0 1 1 0 1	
	0 1 2 3 4 329 330 331 332 333	Age 42 54 63 78 42 59 41 54 74 66	Gender 1 1 1 1 1 1 1 1 1 0 0 0 0	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510 0.286380 ER status 1 1 1	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680 1.39980 PR status 1	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570 0.318830	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8 -0.1 0.8	48340 607320 10815 32190 90210 880320 623870 657860 .07820	y_type \ 3 3 0	1 1 1 0 1 1 0 1	
	0 1 2 3 4 329 330 331 332 333	Age 42 54 63 78 42 59 41 54 74 66	Gender 1 1 1 1 1 logy F 0 0 0 0	Protein1 0.952560 0.000000 -0.523030 -0.876180 0.226110 0.024598 0.100120 0.753820 0.972510 0.286380 CR status 1 1 1 1	2.15000 1.38020 1.76400 0.12943 1.74910 1.40050 -0.46547 1.64250 1.42680 1.39980 PR status 1 1	0.007972 -0.498030 -0.370190 -0.370380 -0.543970 0.024751 0.472370 -0.332850 -0.366570 0.318830	-0.0 -0.5 0.0 0.1 -0.3 0.2 -0.5 0.8 -0.1 0.8	48340 607320 10815 32190 90210 880320 623870 657860 .07820	y_type \ 3 3 0 3	1 1 1 0 1 1 0 1	

```
331
                  0
                                                       0
                                                                      2
                              1
                                         1
     332
                                                       0
                                                                      0
                  1
                              1
                                         1
     333
                  0
                              1
                                         1
         Date_of_Surgery Date_of_Last_Visit Patient_Status
     0
               20-May-18
                                   26-Aug-18
     1
               26-Apr-18
                                   25-Jan-19
                                                          0.0
     2
                                                          1.0
               24-Aug-18
                                   08-Apr-20
     3
               16-Nov-18
                                   28-Jul-20
                                                          1.0
               12-Dec-18
     4
                                   05-Jan-19
                                                          1.0
               15-Jan-19
                                   27-Mar-20
     329
                                                          1.0
     330
                                   23-Apr-19
                                                          1.0
               25-Jul-18
     331
               26-Mar-19
                                   11-Oct-19
                                                          0.0
     332
               26-Nov-18
                                   05-Dec-18
                                                          1.0
     333
               04-Feb-19
                                   10-Aug-19
                                                          0.0
     [334 rows x 15 columns]
[4]: y=df['Patient_Status']
     у
[4]: 0
            1.0
            0.0
     1
     2
            1.0
     3
            1.0
     4
            1.0
     329
            1.0
     330
            1.0
     331
            0.0
     332
            1.0
     333
            0.0
     Name: Patient_Status, Length: 334, dtype: float64
[5]: x=df.drop(['Patient_Status', 'Date_of_Last_Visit', 'Date_of_Surgery'],axis=1)
[5]:
               Gender Protein1 Protein2 Protein3 Protein4
          Age
                                                                 Tumour_Stage
                                                                               \
           42
                       0.952560
     0
                                   2.15000 0.007972 -0.048340
                                                                             1
     1
           54
                       0.000000
                                   1.38020 -0.498030 -0.507320
     2
           63
                     1 -0.523030
                                   1.76400 -0.370190 0.010815
                                                                             1
     3
           78
                     1 -0.876180
                                   0.12943 -0.370380
                                                      0.132190
                                                                             0
                     1 0.226110
                                   1.74910 -0.543970 -0.390210
           42
                                                                             1
     329
           59
                     1 0.024598
                                   1.40050 0.024751 0.280320
                                                                             1
```

330

0

1

1

1

1

```
330
     41
               1 0.100120 -0.46547 0.472370 -0.523870
                                                                      0
331
     54
               1 0.753820 1.64250 -0.332850 0.857860
                                                                      1
332
     74
               1 0.972510 1.42680 -0.366570 -0.107820
                                                                      1
333
                             1.39980 0.318830 0.836050
      66
               1 0.286380
                                                                      1
    Histology ER status PR status HER2 status
                                                   Surgery_type
0
            0
                        1
                                   1
1
             0
                        1
                                   1
                                                0
                                                               3
2
             0
                                                               0
                        1
                                   1
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3
             0
                        1
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                                                               3
4
             0
                        1
329
             0
                        1
                                   1
                                                1
                                                               0
330
             0
                        1
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                                                1
                                                               1
331
             0
                        1
                                   1
                                                0
332
                                                0
                                                               0
             1
                        1
                                   1
333
                                                0
             0
                        1
                                   1
```

[334 rows x 12 columns]

```
[41]: from sklearn.model_selection import train_test_split
      from sklearn.neighbors import KNeighborsClassifier
      from sklearn.preprocessing import StandardScaler
      from sklearn.metrics import accuracy_score
      def diff_train_knn(x, y, test_sizes, random_state):
          results = {}
          for test_size in test_sizes:
              print(f"\nTest Size: {test size}")
              results[test_size] = {}
              x_train, x_test, y_train, y_test = train_test_split(x, y,__
       stest_size=test_size, random_state=random_state)
              scaler = StandardScaler()
              x_train = scaler.fit_transform(x_train)
              x_test = scaler.transform(x_test)
              for n in range(1, 21):
                  model = KNeighborsClassifier(n_neighbors=n)
                  model.fit(x train, y train)
                  y_pred = model.predict(x_test)
                  accuracy = accuracy_score(y_test, y_pred)
                  print(f"n = {n}, Accuracy = {accuracy:.4f}")
                  results[test_size][n] = accuracy
          return results
      test_sizes = [0.2, 0.25, 0.3, 0.35]
      results = diff_train_knn(x, y, test_sizes, random_state=42)
```

Test Size: 0.2

- n = 1, Accuracy = 0.7164
- n = 2, Accuracy = 0.5075
- n = 3, Accuracy = 0.6418
- n = 4, Accuracy = 0.5821
- n = 5, Accuracy = 0.7164
- n = 6, Accuracy = 0.6866
- n = 7, Accuracy = 0.7313
- n = 8, Accuracy = 0.7015
- n = 9, Accuracy = 0.7313
- n = 10, Accuracy = 0.7015
- n = 11, Accuracy = 0.7313
- n = 12, Accuracy = 0.6866
- n = 13, Accuracy = 0.7463
- n = 14, Accuracy = 0.7015
- n = 15, Accuracy = 0.7761
- n = 16, Accuracy = 0.7463
- n = 17, Accuracy = 0.7761
- n = 18, Accuracy = 0.7761
- n = 19, Accuracy = 0.7761
- n = 20, Accuracy = 0.7612

Test Size: 0.25

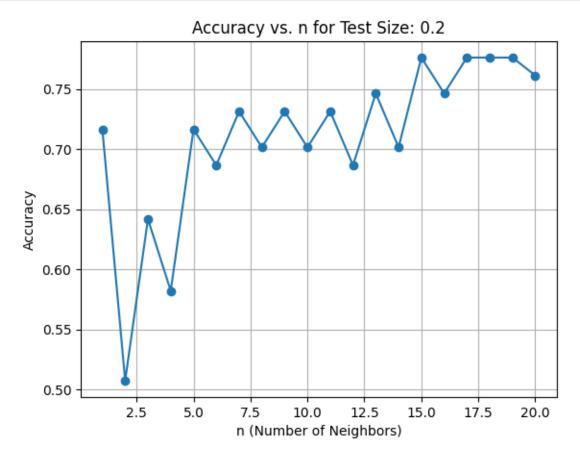
- n = 1, Accuracy = 0.6548
- n = 2, Accuracy = 0.4881
- n = 3, Accuracy = 0.6548
- n = 4, Accuracy = 0.5714
- n = 5, Accuracy = 0.6667
- n = 6, Accuracy = 0.6310
- n = 7, Accuracy = 0.7024
- n = 8, Accuracy = 0.6905
- n = 9, Accuracy = 0.7143
- n = 10, Accuracy = 0.6786
- n = 11, Accuracy = 0.7143
- n = 12, Accuracy = 0.6786
- n = 13, Accuracy = 0.7262
- n = 14, Accuracy = 0.6786
- n = 15, Accuracy = 0.7619
- n = 16, Accuracy = 0.7262
- n = 17, Accuracy = 0.7738
- n = 18, Accuracy = 0.7381
- n = 19, Accuracy = 0.7619
- n = 20, Accuracy = 0.7619

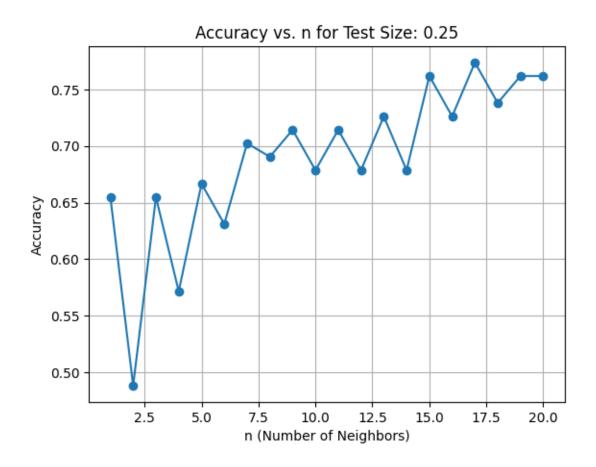
Test Size: 0.3

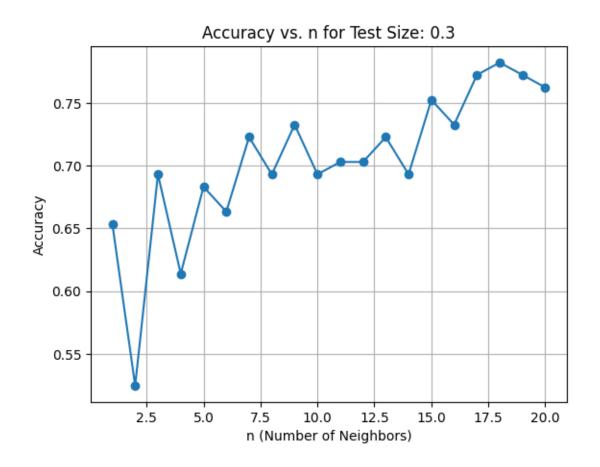
- n = 1, Accuracy = 0.6535
- n = 2, Accuracy = 0.5248

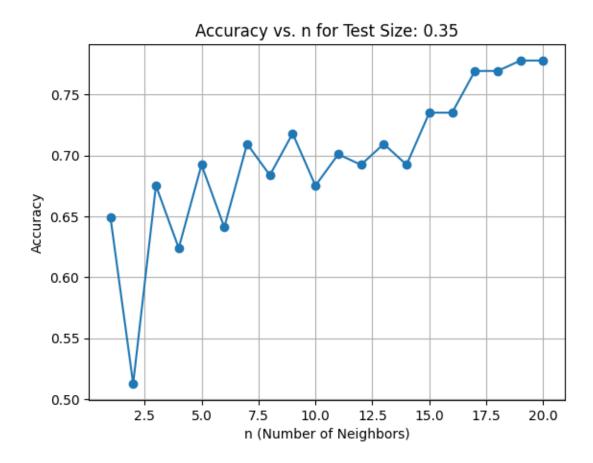
```
n = 3, Accuracy = 0.6931
     n = 4, Accuracy = 0.6139
     n = 5, Accuracy = 0.6832
     n = 6, Accuracy = 0.6634
     n = 7, Accuracy = 0.7228
     n = 8, Accuracy = 0.6931
     n = 9, Accuracy = 0.7327
     n = 10, Accuracy = 0.6931
     n = 11, Accuracy = 0.7030
     n = 12, Accuracy = 0.7030
     n = 13, Accuracy = 0.7228
     n = 14, Accuracy = 0.6931
     n = 15, Accuracy = 0.7525
     n = 16, Accuracy = 0.7327
     n = 17, Accuracy = 0.7723
     n = 18, Accuracy = 0.7822
     n = 19, Accuracy = 0.7723
     n = 20, Accuracy = 0.7624
     Test Size: 0.35
     n = 1, Accuracy = 0.6496
     n = 2, Accuracy = 0.5128
     n = 3, Accuracy = 0.6752
     n = 4, Accuracy = 0.6239
     n = 5, Accuracy = 0.6923
     n = 6, Accuracy = 0.6410
     n = 7, Accuracy = 0.7094
     n = 8, Accuracy = 0.6838
     n = 9, Accuracy = 0.7179
     n = 10, Accuracy = 0.6752
     n = 11, Accuracy = 0.7009
     n = 12, Accuracy = 0.6923
     n = 13, Accuracy = 0.7094
     n = 14, Accuracy = 0.6923
     n = 15, Accuracy = 0.7350
     n = 16, Accuracy = 0.7350
     n = 17, Accuracy = 0.7692
     n = 18, Accuracy = 0.7692
     n = 19, Accuracy = 0.7778
     n = 20, Accuracy = 0.7778
[42]: import matplotlib.pyplot as plt
     for test_size, accuracy_dict in results.items():
       n_values = list(accuracy_dict.keys())
       accuracy_values = list(accuracy_dict.values())
       plt.figure()
       plt.plot(n_values, accuracy_values, marker='o')
```

```
plt.title(f"Accuracy vs. n for Test Size: {test_size}")
plt.xlabel("n (Number of Neighbors)")
plt.ylabel("Accuracy")
plt.grid(True)
plt.show()
```









```
[37]: 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=0)
    from sklearn.svm import SVC
    svc=SVC()
    svc.fit(x_train,y_train)
    y_pred=svc.predict(x_test)
    from sklearn.metrics import accuracy_score
    accuracy_score(y_test,y_pred)
```

[37]: 0.7313432835820896

```
[38]: 0.7261904761904762
```

```
[39]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=0)
    from sklearn.svm import SVC
    svc=SVC()
    svc.fit(x_train,y_train)
    y_pred=svc.predict(x_test)
    from sklearn.metrics import accuracy_score
    accuracy_score(y_test,y_pred)
```

[39]: 0.7326732673267327

[40]: 0.7606837606837606

[]: