```
import pandas as pd
In [1]:
         import matplotlib.pyplot as plt
         import seaborn as sns
         import numpy as np
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import roc_curve, auc
         from sklearn.metrics import classification_report
         from sklearn.metrics import confusion_matrix
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import r2_score,accuracy_score
         from sklearn.svm import SVC
         from sklearn.naive_bayes import GaussianNB
         from sklearn.preprocessing import LabelEncoder
         from sklearn.metrics import accuracy_score
         import warnings
        warnings.filterwarnings('ignore')
        train_set = pd.read_csv(r"C:\Users\kunal perane\Downloads\Training.csv.zip")
In [2]:
         test_set = pd.read_csv(r"C:\Users\kunal perane\Downloads\Testing.csv")
         train_set = train_set.iloc[:,:-1]
         train_set.head()
           itching skin_rash nodal_skin_eruptions continuous_sneezing shivering chills joint_pain stomach_pain
Out[2]:
        0
               1
                         1
                                           1
                                                             0
                                                                      0
                                                                            0
                                                                                     0
                                                                                                  0
        1
               0
                         1
                                           1
                                                             0
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                                                                            0
                                                                                      0
        2
               1
                         0
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                                                                      0
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                                                                                                  0
        3
                                           0
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               1
                         1
                                                             0
               1
                         1
                                           1
                                                             0
                                                                      0
                                                                            0
                                                                                      0
                                                                                                  0
        5 rows × 133 columns
         train_set.shape
In [3]:
         (4920, 133)
Out[3]:
In [4]:
         test_set.shape
         (42, 133)
Out[4]:
```

In [5]:

train_set.describe()

:		itching	skin_rash	nodal_skin_eruptions	continuous_sneezing	shivering	chills	joint_
	count	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000	4920.00
	mean	0.137805	0.159756	0.021951	0.045122	0.021951	0.162195	0.13
	std	0.344730	0.366417	0.146539	0.207593	0.146539	0.368667	0.34
	min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
	25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
	50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
	75%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
	max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00

8 rows × 132 columns

TH [0]: rest_set.describe(In	[6]:	<pre>test_set.describe()</pre>
----------------------------	----	------	--------------------------------

Out[5]:

Out[6]:		itching	skin_rash	nodal_skin_eruptions	continuous_sneezing	shivering	chills	joint_pain	stom
	count	42.000000	42.000000	42.000000	42.000000	42.000000	42.000000	42.000000	4
	mean	0.166667	0.190476	0.023810	0.047619	0.023810	0.166667	0.142857	
	std	0.377195	0.397437	0.154303	0.215540	0.154303	0.377195	0.354169	
	min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
	25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
	50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
	75%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
	max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 132 columns

In [7]: train_set.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4920 entries, 0 to 4919

Columns: 133 entries, itching to prognosis

dtypes: int64(132), object(1)

memory usage: 5.0+ MB

In [8]: test_set.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 42 entries, 0 to 41

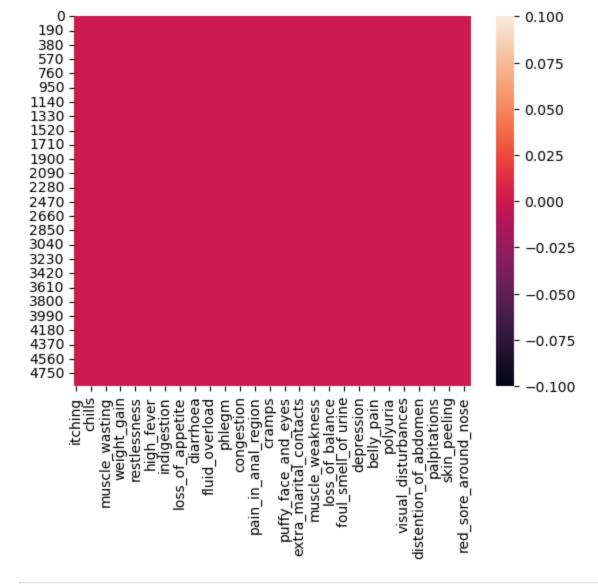
Columns: 133 entries, itching to prognosis

dtypes: int64(132), object(1)

memory usage: 43.8+ KB

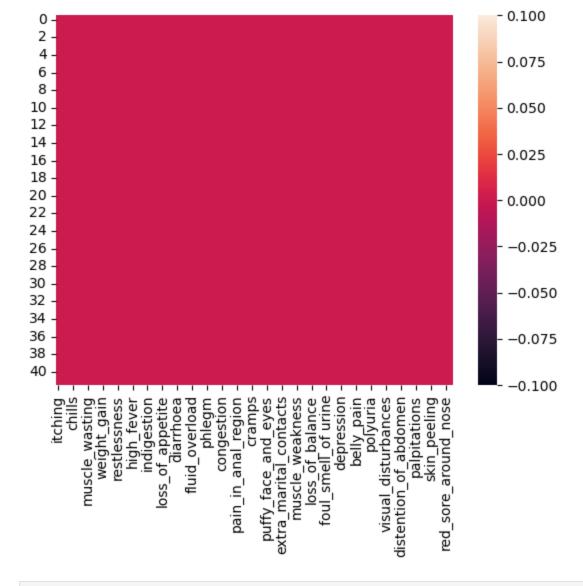
In [9]: train_set.tail(3)

Out[9]:		itching	skin_rash	nodal_skin_eruption	s continuous_sneezin	g shiverin	g chills	joint_pain	stomach_pain
	4917	0	0	1	0	0	0 0	0	0
	4918	0	1	(0	0	0 0	1	0
	4919	0	1		0	0	0 0	0	0
	3 rows	× 133 c	columns						
In [10]:	test_	_set.ta	ail(4)						
Out[10]:	ito	ching s	kin_rash n	odal_skin_eruptions	continuous_sneezing	shivering	chills j	oint_pain	stomach_pain &
	38	0	0	0	0	0	0	0	0
	39	0	1	0	0	0	0	1	0
	40	0	1	0	0	0	0	0	0
	41	1	1	0	0	0	0	0	0
	4 rows	× 133 c	columns						
In [11]:	trair	_set.i	isnull().s	sum()					
Out[11]:	infla blist red_s yello progn	rash _skin_ nuous_ ring .mmator er ore_ar w_crus	eruptions sneezing y_nails ound_nose t_ooze	0 0 0 0 0 0					
In [12]:	test_	_set.is	snull().su	ım()					
Out[12]:	infla blist red_s yello progn	rash _skin_ nuous_ ring .mmator er ore_ar w_crus	eruptions sneezing y_nails ound_nosest_ooze dtype:	0 0 0 0 0 0					
In [13]:	sns.h	neatmap	(train_se	et.isnull())					
Out[13]:	<axes< th=""><th>: ></th><th></th><th></th><th></th><th></th><th></th><th></th><th></th></axes<>	: >							



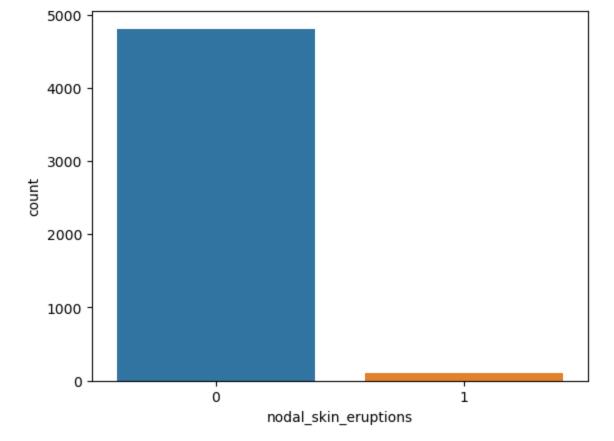
In [14]: sns.heatmap(test_set.isnull())

Out[14]: <Axes: >



In [15]: sns.countplot(x=train_set['nodal_skin_eruptions'])

Out[15]: <Axes: xlabel='nodal_skin_eruptions', ylabel='count'>

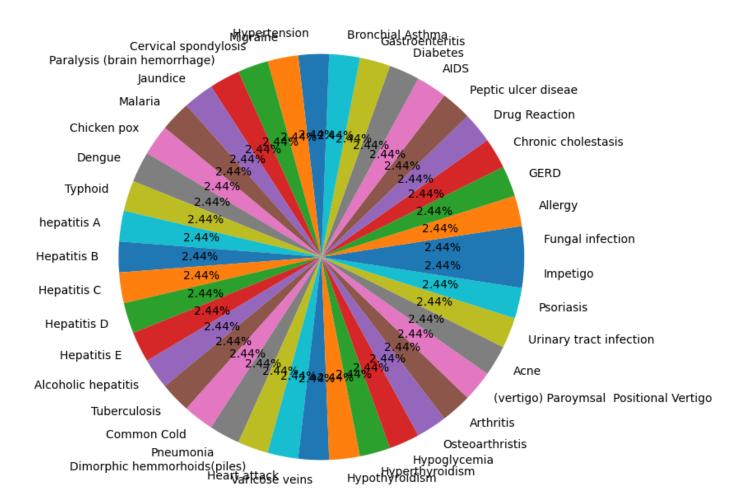


In [16]:	tes	test_set.head()										
Out[16]:	it	ching	skin_rash	nodal_skin_eruptions	continuous_sneezing	shivering	chills	joint_pain	stomach_pain	ac		
	0	1	1	1	0	0	0	0	0			
	1	0	0	0	1	1	1	0	0			
	2	0	0	0	0	0	0	0	1			
	3	1	0	0	0	0	0	0	0			
	4	1	1	0	0	0	0	0	1			

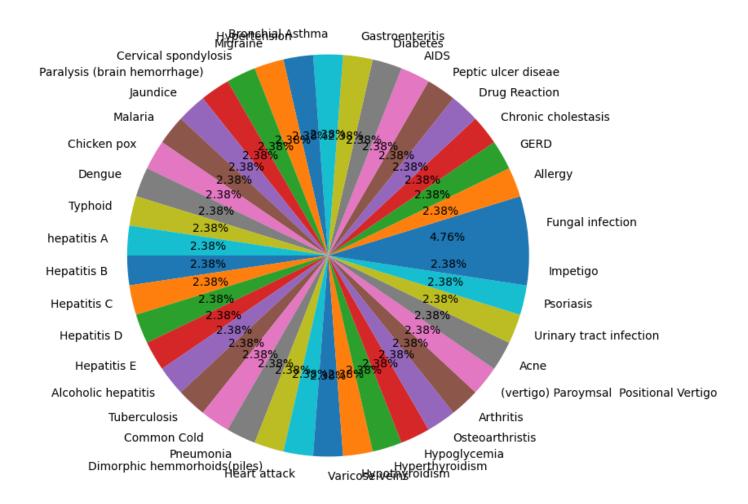
5 rows × 133 columns

17]: train_set.dt	types	
17]: itching	int64	
skin_rash	int64	
nodal_skin_e	ruptions int64	
continuous_s	neezing int64	
shivering	int64	
inflammatory	_nails int64	
blister	int64	
red_sore_aro	und_nose int64	
yellow_crust	_ooze int64	
prognosis	object	
Length: 133,	dtype: object	

```
itching
                                    int64
Out[18]:
         skin_rash
                                    int64
         nodal_skin_eruptions
                                    int64
         continuous_sneezing
                                    int64
         shivering
                                    int64
                                    . . .
         inflammatory_nails
                                    int64
         blister
                                    int64
         red_sore_around_nose
                                    int64
         yellow_crust_ooze
                                    int64
         prognosis
                                   object
         Length: 133, dtype: object
In [19]:
          train_set.nunique()
         itching
                                    2
Out[19]:
                                    2
         skin_rash
                                    2
         nodal_skin_eruptions
                                    2
         continuous_sneezing
                                    2
         shivering
                                   . .
         inflammatory_nails
                                    2
         blister
                                    2
                                    2
         red_sore_around_nose
                                    2
         yellow_crust_ooze
         prognosis
                                   41
         Length: 133, dtype: int64
          test_set.nunique()
In [20]:
                                    2
         itching
Out[20]:
                                    2
         skin_rash
                                    2
         nodal_skin_eruptions
                                    2
         continuous_sneezing
         shivering
                                    2
         inflammatory_nails
                                    2
         blister
                                    2
         red_sore_around_nose
                                    2
         yellow_crust_ooze
                                    2
         prognosis
                                   41
         Length: 133, dtype: int64
In [21]:
         plt.figure(figsize=(8, 8))
          plt.pie(train_set['prognosis'].value_counts(), labels=train_set['prognosis'].unique(), a
          plt.show()
```

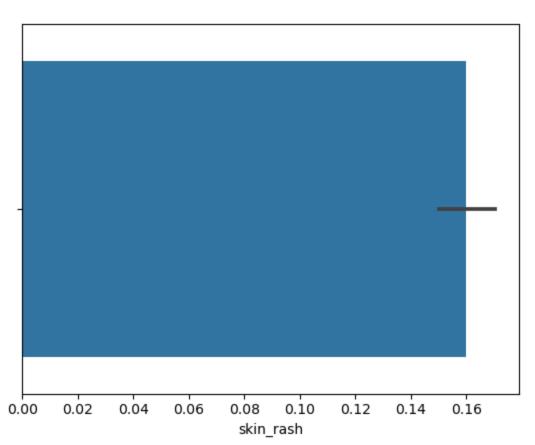


```
In [22]: plt.figure(figsize=(8, 8))
    plt.pie(test_set['prognosis'].value_counts(), labels=test_set['prognosis'].unique(), aut
    plt.show()
```





Out[23]: <Axes: xlabel='skin_rash'>



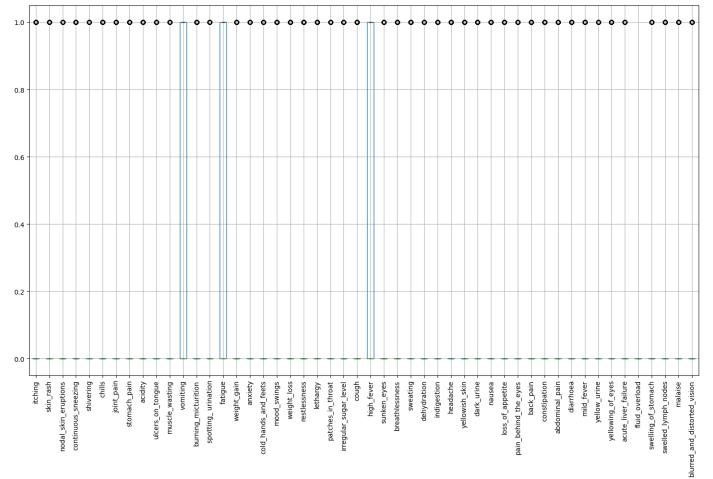
```
In [24]: train_set['prognosis'].value_counts()
            Fungal infection
                                                         120
  Out[24]:
            Hepatitis C
                                                         120
            Hepatitis E
                                                         120
            Alcoholic hepatitis
                                                         120
                                                         120
            Tuberculosis
            Common Cold
                                                         120
            Pneumonia
                                                         120
            Dimorphic hemmorhoids(piles)
                                                         120
            Heart attack
                                                         120
            Varicose veins
                                                         120
            Hypothyroidism
                                                         120
            Hyperthyroidism
                                                         120
            Hypoglycemia
                                                         120
            Osteoarthristis
                                                         120
            Arthritis
                                                         120
            (vertigo) Paroymsal Positional Vertigo
                                                         120
                                                         120
            Urinary tract infection
                                                         120
            Psoriasis
                                                         120
            Hepatitis D
                                                         120
                                                         120
            Hepatitis B
            Allergy
                                                         120
            hepatitis A
                                                         120
            GERD
                                                         120
            Chronic cholestasis
                                                         120
                                                         120
            Drug Reaction
            Peptic ulcer diseae
                                                         120
            AIDS
                                                         120
            Diabetes
                                                         120
            Gastroenteritis
                                                         120
            Bronchial Asthma
                                                         120
            Hypertension
                                                         120
            Migraine
                                                         120
            Cervical spondylosis
                                                         120
            Paralysis (brain hemorrhage)
                                                         120
            Jaundice
                                                         120
            Malaria
                                                         120
                                                         120
            Chicken pox
            Dengue
                                                         120
            Typhoid
                                                         120
                                                         120
            Impetigo
            Name: prognosis, dtype: int64
            print(f'**Summary**:\n There are 41 diseases in the dataset and each containing 120 rows
  In [25]:
            **Summary**:
             There are 41 diseases in the dataset and each containing 120 rows. So, the dataset is e
            qually balanced.
  In [26]:
            total = train_set.isnull().sum().sort_values(ascending=False)
            percent = (train_set.isnull().sum()/train_set.isnull().count()).sort_values(ascending=Fa
            missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
            total = train_set.isna().sum().sort_values(ascending=False)
            percent = (train_set.isna().sum()/train_set.isna().count()).sort_values(ascending=False)
            na_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
            if((na_data.all()).all()>0 or (na_data.all()).all()>0):
                  print('Found Missing Data or NA values')
            else:
                <u>print('There</u> is no missing data or null values in the collected data. Additionally,
Loading [MathJax]/extensions/Safe.js
```

There is no missing data or null values in the collected data. Additionally, the length of each column is same.

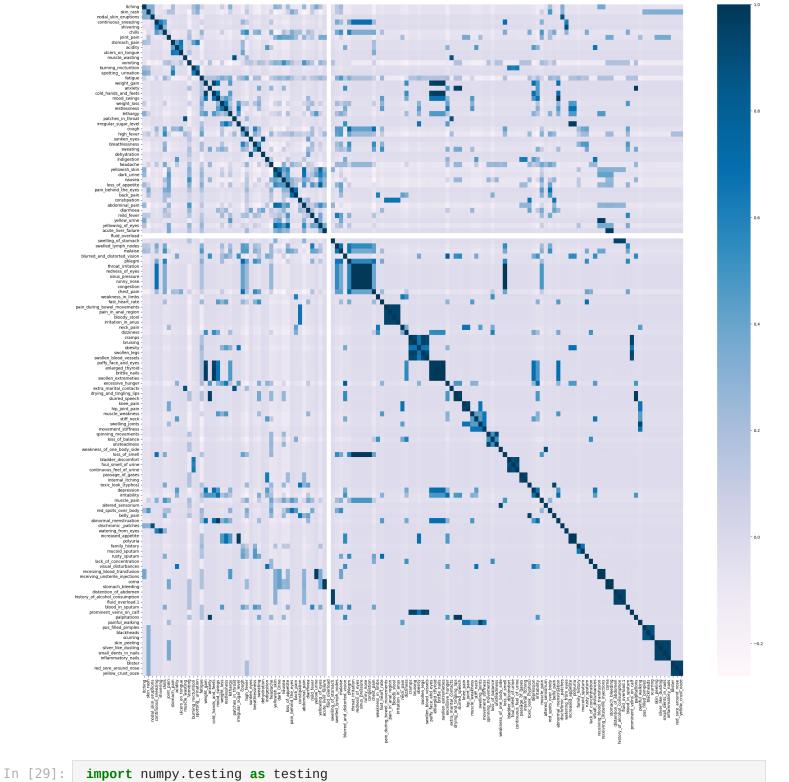
```
In [27]: temp_df=train_set.iloc[:,:-1]
#Detect outliers
plt.subplots(figsize=(18,10))
temp_df.iloc[:,:50].boxplot()
plt.xticks(rotation=90)
plt.show()

plt.subplots(figsize=(18,10))
temp_df.iloc[:,50:].boxplot()
plt.xticks(rotation=90)
plt.show()

print(f'**Summary**:\n No outliers')
```



```
0.8
                       0.6
                       0.4
                       0.2
                       0.0
                                                                                                              swelling joints
movement stiffness
spinning_movements
loss_of_balance
unsteadiness
weakness_of_one_body_side
lbadder_discomfort -
foul smell_of urine -
passage_of_gases
internal_itching
toxic_look_(ftyphos)
                                                                                                                                                                                                 stomach bleeding
distention of abdomen
history_of_alcohol_consumption
fluid_overhoad.1
blood_in_sprutum
prominent_veins_on_calf
palpitations
painful_walking
painful_walking
painful_walking
painful_walking
blackfreade.
                                                                                                                                                      muscle_pain
altered_sensorium
red_spots_over_body
belly_pain
                       **Summary**:
                         No outliers
                       plt.figure(figsize = (30, 30))
In [28]:
                        sns.heatmap(train_set.corr(), cmap = 'PuBu', annot = False)
                       plt.show()
```



```
In [30]:
         corr_matrix=train_set.corr()
          upper =upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
upper
```

Out[30]:		itching	skin_rash	nodal_skin_eruptions	continuous_sneezing	shivering	chills	join		
	itching	NaN	0.318158	0.326439	-0.086906	-0.059893	-0.175905	-0.1		
	skin_rash	NaN	NaN	0.298143	-0.094786	-0.065324	-0.029324	0.1		
	nodal_skin_eruptions	NaN	NaN	NaN	-0.032566	-0.022444	-0.065917	-0.C		
	continuous_sneezing	NaN	NaN	NaN	NaN	0.608981	0.446238	-0.0		
	shivering	NaN	NaN	NaN	NaN	NaN	0.295332	-O.C		
	small_dents_in_nails	NaN	NaN	NaN	NaN	NaN	NaN			
	inflammatory_nails	NaN	NaN	NaN	NaN	NaN	NaN			
	blister	NaN	NaN	NaN	NaN	NaN	NaN			
	red_sore_around_nose	NaN	NaN	NaN	NaN	NaN	NaN			
	yellow_crust_ooze	NaN	NaN	NaN	NaN	NaN	NaN			
	132 rows × 132 column	S								
In [31]:	<pre>to_drop = [column for column in upper.columns if any(upper[column] > 0.9)] print(to_drop,len(to_drop))</pre>									
	<pre>train_set=train_set.drop(to_drop, axis=1) test_set=test_set.drop(to_drop, axis=1)</pre>									
	['cold_hands_and_feets', 'redness_of_eyes', 'sinus_pressure', 'runny_nose', 'congestio n', 'pain_in_anal_region', 'bloody_stool', 'irritation_in_anus', 'bruising', 'swollen_le gs', 'swollen_blood_vessels', 'puffy_face_and_eyes', 'enlarged_thyroid', 'brittle_nail states and the states are th									

```
train_set=train_set.drop(to_drop, axis=1)
    test_set=test_set.drop(to_drop, axis=1)

['cold_hands_and_feets', 'redness_of_eyes', 'sinus_pressure', 'runny_nose', 'congestio
    n', 'pain_in_anal_region', 'bloody_stool', 'irritation_in_anus', 'bruising', 'swollen_le
    gs', 'swollen_blood_vessels', 'puffy_face_and_eyes', 'enlarged_thyroid', 'brittle_nail
    s', 'swollen_extremeties', 'drying_and_tingling_lips', 'slurred_speech', 'hip_joint_pai
    n', 'unsteadiness', 'loss_of_smell', 'continuous_feel_of_urine', 'internal_itching', 'al
    tered_sensorium', 'belly_pain', 'abnormal_menstruation', 'increased_appetite', 'polyuri
    a', 'receiving_blood_transfusion', 'receiving_unsterile_injections', 'coma', 'stomach_bl
    eeding', 'distention_of_abdomen', 'history_of_alcohol_consumption', 'fluid_overload.1',
    'prominent_veins_on_calf', 'palpitations', 'painful_walking', 'silver_like_dusting', 'sm
    all_dents_in_nails', 'inflammatory_nails', 'red_sore_around_nose', 'yellow_crust_ooze']

In [32]: temp_train=train_set.iloc[:,:-1]

In [33]: from sklearn.feature_selection import VarianceThreshold

In [34]: sel = VarianceThreshold(threshold=0.03)
```

```
In [34]: sel = VarianceThreshold(threshold=0.03)
    sel.fit(temp_train)
```

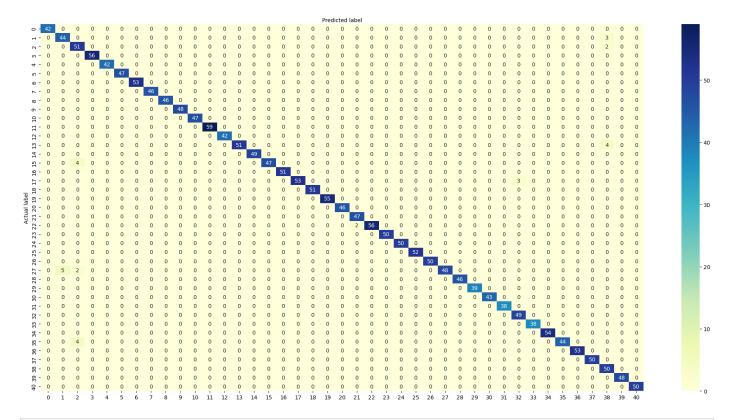
Out[34]: ▼ VarianceThreshold

VarianceThreshold(threshold=0.03)

```
In [35]: print(
    len([
        x for x in temp_train.columns
        if x not in temp_train.columns[sel.get_support()]
    ]))

to_drop=[x for x in temp_train.columns if x not in temp_train.columns[sel.get_support()]
    train_set=train_set.drop(to_drop, axis=1)
    test_set=test_set.drop(to_drop, axis=1)
```

```
encoder = LabelEncoder()
In [36]:
         train_set["prognosis"] = encoder.fit_transform(train_set["prognosis"])
         test_set["prognosis"] = encoder.transform(test_set["prognosis"])
In [37]: X_train, X_valid, y_train, y_valid = train_test_split(train_set.drop('prognosis', 1), tr
In [38]: X_train.shape
         (2952, 49)
Out[381:
In [391:
         test_set = pd.concat([test_set,pd.concat([X_valid,y_valid],axis=1)],axis=0)
         test_set.shape
         (2010, 50)
Out[391:
In [40]:
         svm = SVC()
         svm.fit(X_train, y_train)
         y_pred=svm.predict(X_valid)
         print("SVM Train score with ",format(svm.score(X_train, y_train)))
         SVM Train score with 0.9854336043360433
In [41]: print("SVM Test score with ",format(svm.score(test_set.iloc[:,:-1], test_set['prognosis'
         SVM Test score with 0.9855721393034826
In [42]: y_pred = svm.predict(test_set.iloc[:,:-1])
         class_names=encoder.classes_
         fig, ax = plt.subplots(figsize = (20,10))
         tick_marks = np.arange(len(class_names))
         plt.xticks(tick_marks, class_names)
         plt.yticks(tick_marks, class_names)
         cm = confusion_matrix(test_set['prognosis'], y_pred)
         sns.heatmap(cm, annot=True, cmap="YlGnBu" ,fmt='g')
         ax.xaxis.set_label_position("top")
         plt.tight_layout()
         plt.title('Confusion matrix', y=1.1)
         plt.ylabel('Actual label')
         plt.xlabel('Predicted label')
         Text(0.5, 885.5555555555555, 'Predicted label')
Out[42]:
```



In [43]: print(classification_report(test_set['prognosis'], y_pred))

```
0
                                1.00
                                           1.00
                                                      1.00
                                                                    42
                       1
                                0.90
                                                                    47
                                           0.94
                                                       0.92
                       2
                                0.84
                                           0.96
                                                      0.89
                                                                    53
                       3
                                1.00
                                           1.00
                                                       1.00
                                                                    56
                       4
                                1.00
                                           1.00
                                                       1.00
                                                                    42
                       5
                                1.00
                                           1.00
                                                      1.00
                                                                    47
                       6
                                1.00
                                                                    53
                                           1.00
                                                       1.00
                       7
                                1.00
                                                                    46
                                           1.00
                                                      1.00
                       8
                                1.00
                                           1.00
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                                                                    46
                       9
                                1.00
                                           1.00
                                                                    48
                                                      1.00
                      10
                                1.00
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                      11
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                                           1.00
                                                       1.00
                                                                    59
                      12
                                1.00
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                      13
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                                                      0.96
                                                                    55
                      14
                                                                    49
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                                                       1.00
                      15
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                                           0.92
                                                      0.96
                                                                    51
                      16
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                                                                    51
                      17
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                                           0.95
                                                      0.97
                                                                    56
                      18
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                      19
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                                           1.00
                                                       1.00
                      20
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                                           1.00
                                                      1.00
                                                                    46
                      21
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                                                       0.98
                                                                    47
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                                                      0.98
                                                                    58
                      23
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                                           1.00
                                                      1.00
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                                           0.87
                                                       0.93
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                      28
                                1.00
                                           1.00
                                                      1.00
                                                                    46
                      29
                                1.00
                                           1.00
                                                                    39
                                                      1.00
                      30
                                1.00
                                           1.00
                                                      1.00
                                                                    43
                      31
                                                                    38
                                1.00
                                           1.00
                                                      1.00
                      32
                                0.94
                                           1.00
                                                       0.97
                                                                    49
                      33
                                1.00
                                           1.00
                                                                    38
                                                      1.00
                      34
                                1.00
                                           1.00
                                                      1.00
                                                                    54
                      35
                                1.00
                                           0.92
                                                      0.96
                                                                    48
                      36
                                1.00
                                           1.00
                                                      1.00
                                                                    53
                      37
                                1.00
                                           1.00
                                                      1.00
                                                                    50
                      38
                                                                    50
                                0.85
                                           1.00
                                                      0.92
                      39
                                1.00
                                           1.00
                                                       1.00
                                                                    48
                      40
                                1.00
                                           1.00
                                                       1.00
                                                                    50
               accuracy
                                                       0.99
                                                                  2010
                                                       0.99
                                                                  2010
              macro avg
                                0.99
                                           0.99
          weighted avg
                                0.99
                                           0.99
                                                       0.99
                                                                  2010
In [44]:
          cm = confusion_matrix(test_set['prognosis'], y_pred)
          print('Confusion Matrix:')
          print(cm)
          Confusion Matrix:
                                   0]
          [[42
                0
                    0 ...
                                0
           [ 0 44 0 ...
                                   0]
                            3
                                0
             0
                 0 51 ...
                            2
                                   0]
           0
                 0
                    0 ... 50
                                0
                                   0]
             0
                 0
                    0 ...
                            0
                              48
                                   0]
           0
                 0
                    0 ...
                            0
                                0 50]]
          plt.figure(figsize = (40, 40))
          sns.heatmap(cm, annot=True)
```

recall

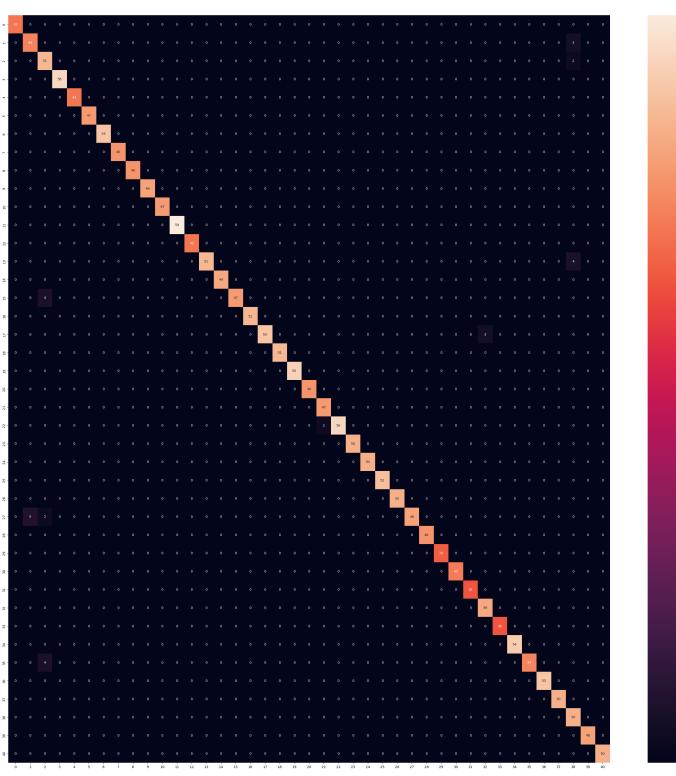
precision

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f1-score

support

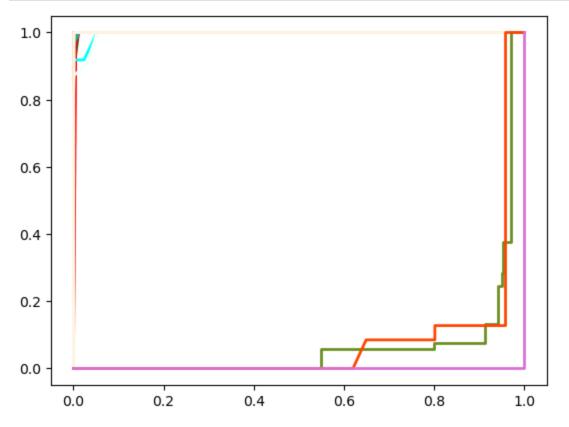
Out[45]: <Axes: >



```
In [46]: from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier

In [47]: yb=label_binarize(test_set['prognosis'], classes=[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,1]
In [48]: nc=yb.shape[1]
In [49]: classifier=OneVsRestClassifier(SVC(kernel='linear', probability=True, random_state=42))
In [50]: svm_classifier = SVC(probability=True)
svm_classifier.fit(X_train, y_train)
```

```
Out[50]: ▼
                     SVC
           SVC(probability=True)
  In [51]: y_score = svm_classifier.decision_function(X_valid)
           print("y_score for the first 5 samples:")
  In [52]:
            print(y_score[:5])
           y_score for the first 5 samples:
           [[21.86158193 35.31605563 40.32520354 28.28737217 34.31223023 26.2773816
             18.72010354 23.80368093 7.68847269 15.69353494 2.68514062 0.6854393
             14.69406504 30.31388998 29.30826924 38.32432379 19.71490952 32.31165209
             21.83163656 8.68730457 17.70207148 9.68787455 3.68495509 23.82396322
              4.68609704 10.68903078 16.69828844 39.32478612 11.68946481 12.6895649
             13.68998022 27.27823604 33.31492039 22.86124676 5.68613547 36.32254339
             -0.31694068 6.68688946 37.31919178 31.31259668 1.68470662]
            [21.86158193 35.31605563 40.32520354 28.28737217 34.31223023 26.2773816
             18.72010354 23.80368093 7.68847269 15.69353494 2.68514062 0.6854393
             14.69406504 30.31388998 29.30826924 38.32432379 19.71490952 32.31165209
             21.83163656 8.68730457 17.70207148 9.68787455 3.68495509 23.82396322
              4.68609704 10.68903078 16.69828844 39.32478612 11.68946481 12.6895649
             13.68998022 27.27823604 33.31492039 22.86124676 5.68613547 36.32254339
             -0.31694068 6.68688946 37.31919178 31.31259668 1.68470662]
            33.09592164 20.8246673
                                     7.7584857 13.7715227
                                                            6.75441234 3.74867728
             39.28542832 -0.29237315 19.91719316 12.78483245 23.81280433 29.21106443
             35.20265061 9.76684094 25.87805492 13.80556376 9.75123956 20.84572736
             40.32644599 38.27201957 37.25166492 11.73145074 29.9378065 27.89120683
             29.91544485 23.91914853 13.82898978 22.86731409 30.92335255 9.74197989
              4.75287557 18.80637311 4.7149726 32.23466916 6.753724921
             [21.93938204 40.32520406 37.31913306 29.29248036 36.31445246 27.28540627
             26.28979018 23.84769252 4.68848404 13.69317858 3.68823014 0.68532037
             12.69405027 31.31563432 22.84842482 35.31353416 18.7168079 33.31390391
             20.88276728 5.68711185 17.70200242 7.68713147 6.68975368 22.88090956
              2.68599468 9.68891004 14.69845259 38.32212059 16.70363063 15.70380476
             10.68994449 28.28702305 34.31661238 21.94566488 8.69079789 30.30969676
             -0.3161259 11.69561008 39.32077274 32.3145932
                                                             1.68456016]
             [31.27873909 14.70645571 17.71245641 35.31438707 21.75714572 19.73571931
              9.71554899 11.72145241 5.71095854 40.32682363 -0.29851255 7.71178904
              6.7080031 11.70405244 27.94541676 28.24615308 24.7531733 29.2265053
             25.83054034 34.29142775 37.30706834 39.31558273 38.30834713 12.72335083
              0.70204532 9.72688171 4.70611475 14.71304487 32.26477348 13.73244217
              3.70595448 19.73826005 29.25762006 36.30965732 2.70251232 17.71817129
              1.70557798 22.74422509 19.71472817 21.74582191 33.28657843]]
  In [53]: y_valid_binary = label_binarize(y_valid, classes=[0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,
  In [54]: n_classes = y_valid_binary.shape[1]
  In [55]: fpr = dict()
            tpr = dict()
            roc_auc = dict()
  In [56]: for i in range(n_classes):
               fpr[i], tpr[i], _ = roc_curve(y_valid_binary[:, i], y_score[:, i])
               roc_auc[i] = auc(fpr[i], tpr[i])
  In [57]: plt.figure(figsize=(10, 8))
            colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k', 'lime', 'navy', 'orange', 'purple', 'pink'
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```



```
    ROC curve of class 0 (AUC = 1.00)

                                         ROC curve of class 1 (AUC = 1.00)
                                         ROC curve of class 2 (AUC = 1.00)

    ROC curve of class 3 (AUC = 1.00)

    ROC curve of class 4 (AUC = 1.00)

    ROC curve of class 5 (AUC = 1.00)

    ROC curve of class 6 (AUC = 1.00)

    ROC curve of class 7 (AUC = 1.00)

    ROC curve of class 8 (AUC = 1.00)

                                        ROC curve of class 9 (AUC = 1.00)

    ROC curve of class 10 (AUC = 1.00)

                                          ROC curve of class 11 (AUC = 1.00)

    ROC curve of class 12 (AUC = 1.00)

    ROC curve of class 13 (AUC = 1.00)

    ROC curve of class 14 (AUC = 1.00)

                                          ROC curve of class 15 (AUC = 1.00)

    ROC curve of class 16 (AUC = 1.00)

                                          ROC curve of class 17 (AUC = 1.00)
               Receiver Operating C ROC curve of class 18 (AUC = 1.00)
                                          ROC curve of class 19 (AUC = 1.00)
   1.0
                                          ROC curve of class 20 (AUC = 1.00)
                                          ROC curve of class 21 (AUC = 1.00)
                                          ROC curve of class 22 (AUC = 1.00)
   0.8
                                          ROC curve of class 23 (AUC = 1.00)
                                          ROC curve of class 24 (AUC = 1.00)
Frue Positive Rate
                                          ROC curve of class 25 (AUC = 1.00)
   0.6
                                          ROC curve of class 26 (AUC = 1.00)
                                          ROC curve of class 27 (AUC = 1.00)
                                          ROC curve of class 28 (AUC = 1.00)
                                          ROC curve of class 29 (AUC = 1.00)
   0.4
                                          ROC curve of class 30 (AUC = 1.00)
                                          ROC curve of class 31 (AUC = 1.00)
                                          ROC curve of class 32 (AUC = 1.00)
   0.2
                                          ROC curve of class 33 (AUC = 0.07)
                                          ROC curve of class 34 (AUC = 0.08)
                                          ROC curve of class 35 (AUC = 0.00)
   0.0
      0.0
                    0.2
                                   0.4
                                                  0.6
                                                                0.8
                                                                               1.0
                                  False Positive Rate
```

```
grid_search = GridSearchCV(svm, param_grid, cv=5, n_jobs=-1)
In [63]:
         grid_search.fit(X_train, y_train)
         ▶ GridSearchCV
Out[63]:
          ▶ estimator: SVC
                SVC
         print("Best hyperparameters found: ", grid_search.best_params_)
In [64]:
         print("Best accuracy on the validation set: {:.2f}".format(grid_search.best_score_))
         Best hyperparameters found: {'C': 10, 'kernel': 'linear'}
         Best accuracy on the validation set: 0.98
In [65]:
         best_svm = grid_search.best_estimator_
         best_svm.fit(X_train, y_train)
Out[65]:
                      SVC
         SVC(C=10, kernel='linear')
In [66]:
         test_features = test_set.drop('prognosis', axis=1)
         test_accuracy = best_svm.score(test_features, test_set['prognosis'])
         print("Test accuracy: {:.2f}".format(test_accuracy))
         Test accuracy: 0.99
In [67]: from sklearn.model_selection import RandomizedSearchCV
         from scipy.stats import uniform
In [68]:
         svm=SVC(kernel='linear')
         param_dist={
             'C':uniform(loc=0, scale=10),
             'gamma':['scale', 'auto']+list(uniform(loc=0, scale=1).rvs(10)),
In [69]:
         random_search=RandomizedSearchCV(svm,param_distributions=param_dist,n_iter=10,cv=10,n_jo
         random_search.fit(X_train,y_train)
         ▶ RandomizedSearchCV
Out[69]:
            ▶ estimator: SVC
In [70]:
         best_model = random_search.best_estimator_
         best_params = random_search.best_params_
In [71]:
         y_pred = best_model.predict(test_set.iloc[:,:-1])
         accuracy = accuracy_score( test_set['prognosis'], y_pred)
         print('Accuracy:',accuracy)
         print('Classification Report:')
         print(classification_report( test_set['prognosis'],y_pred))
```

Accuracy: 0.9855721393034826

Classification Report:

Classificatio	•			
	precision	recall	f1-score	support
0	1.00	1.00	1.00	42
1	0.90	0.94	0.92	47
2	0.84	0.96	0.89	53
3	1.00	1.00	1.00	56
4	1.00	1.00	1.00	42
5	1.00	1.00	1.00	47
6	1.00	1.00	1.00	53
7	1.00	1.00	1.00	46
8	1.00	1.00	1.00	46
9	1.00	1.00	1.00	48
10	1.00	1.00	1.00	47
11	1.00	1.00	1.00	59
12	1.00	1.00	1.00	42
13	1.00	0.93	0.96	55
14	1.00	1.00	1.00	49
15	1.00	0.92	0.96	51
16	1.00	1.00	1.00	51
17	1.00	0.95	0.97	56
18	1.00	1.00	1.00	51
19	1.00	1.00	1.00	55
20	1.00	1.00	1.00	46
21	0.96	1.00	0.98	47
22	1.00	0.97	0.98	58
23	1.00	1.00	1.00	50
24	1.00	1.00	1.00	50
25	1.00	1.00	1.00	52
26	1.00	1.00	1.00	50
27	1.00	0.87	0.93	55
28 29	1.00	1.00	1.00	46 39
30	1.00 1.00	1.00	1.00	43
31	1.00	1.00 1.00	1.00 1.00	38
32	0.94	1.00	0.97	49
33	1.00	1.00	1.00	38
34	1.00	1.00	1.00	54
35	1.00	0.92	0.96	48
36	1.00	1.00	1.00	53
37	1.00	1.00	1.00	50
38	0.85	1.00	0.92	50
39	1.00	1.00	1.00	48
40	1.00	1.00	1.00	50
accuracy			0.99	2010
macro avg	0.99	0.99	0.99	2010
weighted avg	0.99	0.99	0.99	2010

In [75]: y_pred = naive_bayes_classifier.predict(X_valid)

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