Symptom, Disease, Physician: Who to Visit When You Are Not Feeling Well?

Abstract: Guidance to patient on visiting to the appropriate department is a crucial task during the patient workflow, which means that patient could receive medical intervention well on time if it is accurrate enough. This project use the classification algorithm, including **logistic regressor, random forest, K neighbours classifier, Support Vector Classifier, Gradient Boosting Classifier, and Gaussian Naive Bayes Classifier**, to establish a model on guiding patient on visiting the corresponding department based on their main common symptom.

The data preprocessing is referred from https://www.kaggle.com/code/ebrahimelgazar/disease-recommendation-system

0. Import packages & data (Set up environment when applicable)

In [1]:
```
# import basic packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as st
# !pip install pandasql
import pandasql as ps

# import sqlite3 as lite # maybe this is for google colab
import os
import time
```

In [63]:
```
# import machine-learning based general packages
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB

# This is for confusion matrix
from sklearn import metrics, model_selection
```

In [2]:
```
# set up the environment (for google colab only)


# the data source
# the corresponding file is available at
# https://www.kaggle.com/datasets/ebrahimelgazar/doctor-specialist-recommendation-s

# If you use google colab, PLEASE put the corresponding csv dataset into the root d
# The file will be deleted everytime in google colab!!! And you might use additiona

# If you use jupyter lab, make sure that you set the directory to the place where t

# os.getcwd()
# os.chdir('your directory goes here')
# os.listdir()
disease_description = pd.read_csv('Disease_Description.csv')

doctor_specialist = pd.read_csv('Doctor_Specialist.csv')

doctor_versus_disease = pd.read_csv('Doctor_Versus_Disease.csv', encoding='windows-
                                     header = None, usecols=[0,1], names=['Disease',
# 'utf-8' codec can't decode byte 0xa0 in position 490: invalid start byte
# this table has no title...

original_dataset = pd.read_csv('Original_Dataset.csv')

symptom_weights = pd.read_csv('Symptom_Weights.csv', header = None, usecols = [0, 1
# this table also has no title...
```

In [3]:
```
# show all columns
pd.set_option('display.max_columns', None)
```

1. EDA

1.1 Explore Each Table

Disease description (Disease, Description)

In [4]:
```
# for jupyter notebook, please use pandasql
# for google colab, please set up a connection before using sqlite3.

# first try...
query = '''
    select * from
    disease_description
    limit 5;
'''     # disease_description.head()
ps.sqldf(query)
```

Out[4]:

	Disease	Description
0	Drug Reaction	An adverse drug reaction (ADR) is an injury ca...
1	Malaria	An infectious disease caused by protozoan para...
2	Allergy	An allergy is an immune system response to a f...
3	Hypothyroidism	Hypothyroidism, also called underactive thyroi...
4	Psoriasis	Psoriasis is a common skin disorder that forms...

In [5]:
```
print(disease_description.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41 entries, 0 to 40
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Disease      41 non-null     object
 1   Description  41 non-null     object
dtypes: object(2)
memory usage: 784.0+ bytes
None
```

Doctor Specialist (Doctor Specialist)

In [6]:
```
query = '''
    select * from
    doctor_specialist
    limit 5
'''   # doctor_specialist.head()
ps.sqldf(query)
```

Out[6]:

	Doctor Specialist
0	Dermatologist
1	Allergist
2	Gastroenterologist
3	Hepatologist
4	Osteopathic

In [7]:
```
print(doctor_specialist.info())
print(doctor_specialist.shape)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19 entries, 0 to 18
Data columns (total 1 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Doctor Specialist  19 non-null     object
dtypes: object(1)
memory usage: 280.0+ bytes
None
(19, 1)
```

Doctor versus Disease ~~(Drug Reaction, Allergist)~~(Disease, Doctor_Specialist)

In [8]:
```
query = '''
    select *
    from
    doctor_versus_disease
    limit 5
''' # doctor_versus_disease.head()
ps.sqldf(query)

# This table has no title, the corresponding title must be Disease, Doctor Speciali
```

Out[8]:

	Disease	Doctor_Specialist
0	Drug Reaction	Allergist
1	Allergy	Allergist
2	Hypertension	Cardiologist
3	Heart attack	Cardiologist
4	Psoriasis	Dermatologist

In [9]:
```
doctor_versus_disease.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41 entries, 0 to 40
Data columns (total 2 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   Disease            41 non-null     object
 1   Doctor_Specialist  41 non-null     object
dtypes: object(2)
memory usage: 784.0+ bytes
```

original_dataset (Symptom_1 to Symptom 17)

In [10]:
```
query = '''
    select * from
    original_dataset
    limit 5
''' # original_dataset.head()
ps.sqldf(query)
```

```
# unstructured column-based data, for saving storage
# may be used for train and test
```

Out[10]:

	Disease	Symptom_1	Symptom_2	Symptom_3	Symptom_4	Symptom_5
0	Fungal infection	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	None
1	Fungal infection	skin_rash	nodal_skin_eruptions	dischromic _patches	None	None
2	Fungal infection	itching	nodal_skin_eruptions	dischromic _patches	None	None
3	Fungal infection	itching	skin_rash	dischromic _patches	None	None
4	Fungal infection	itching	skin_rash	nodal_skin_eruptions	None	None

In [11]:

```
original_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4920 entries, 0 to 4919
Data columns (total 18 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Disease     4920 non-null   object
 1   Symptom_1   4920 non-null   object
 2   Symptom_2   4920 non-null   object
 3   Symptom_3   4920 non-null   object
 4   Symptom_4   4572 non-null   object
 5   Symptom_5   3714 non-null   object
 6   Symptom_6   2934 non-null   object
 7   Symptom_7   2268 non-null   object
 8   Symptom_8   1944 non-null   object
 9   Symptom_9   1692 non-null   object
 10  Symptom_10  1512 non-null   object
 11  Symptom_11  1194 non-null   object
 12  Symptom_12  744 non-null    object
 13  Symptom_13  504 non-null    object
 14  Symptom_14  306 non-null    object
 15  Symptom_15  240 non-null    object
 16  Symptom_16  192 non-null    object
 17  Symptom_17  72 non-null     object
dtypes: object(18)
memory usage: 692.0+ KB
```

symptom_weights ~~(abdominal_pain, 1)~~(Symptom, weight)

In [12]:

```
query = '''
    select * from
    symptom_weights
    limit 5
''' # symptom_weights.head()
```

```
ps.sqldf(query)

# no title, the title sould be Symptom and weight, respectively
```

Out[12]:

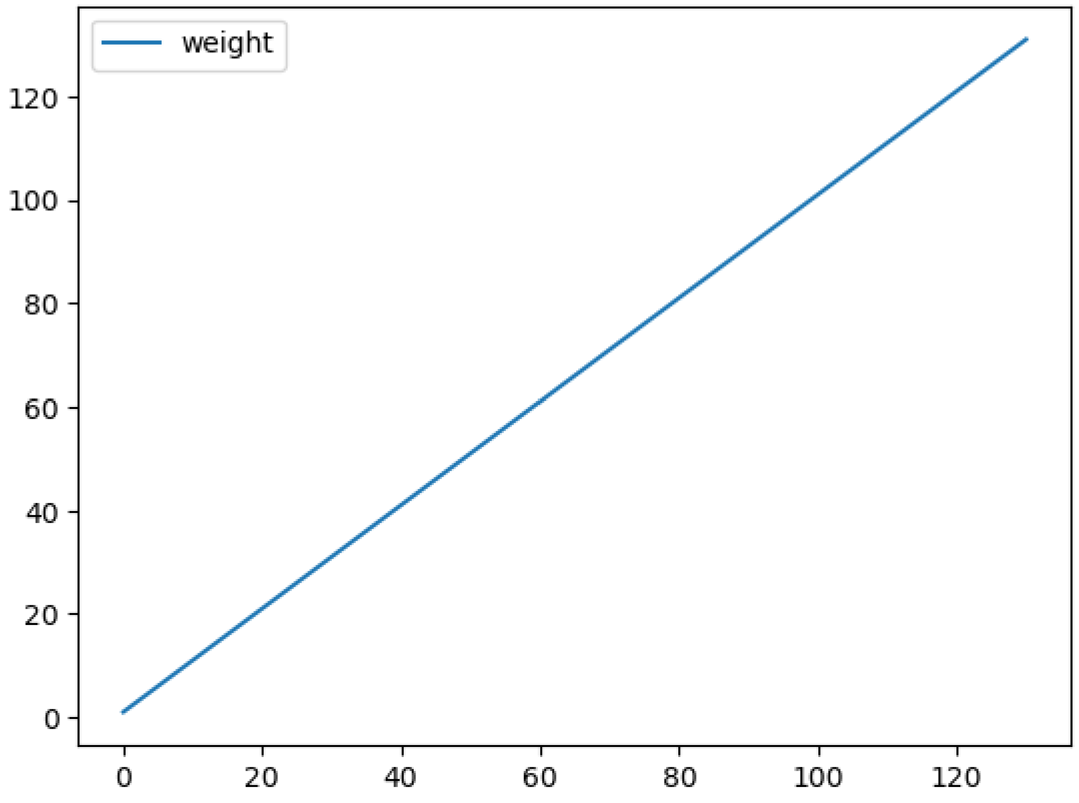
	Symptom	weight
0	abdominal_pain	1
1	abnormal_menstruation	2
2	acidity	3
3	acute_liver_failure	4
4	altered_sensorium	5

In [13]:
```
symptom_weights.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 131 entries, 0 to 130
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   Symptom  131 non-null    object
 1   weight   131 non-null    int64 
dtypes: int64(1), object(1)
memory usage: 2.2+ KB
```

In [14]:
```
sns.lineplot(symptom_weights)
# as we see, the second column (weight) might be id-liked data
```

Out[14]: `<Axes: >`



Stage summary: The data generally seems to be clean, with the `original_dataset` contains column-based training and testing dataset. However, the `doctor_versus_disease` and the `symptom_weights` lack of title row, indicating that we should add the title before query.

Therefore, this project rewined to the beginning of the data to modify the reading method of the latter two tables.

Disease description (Disease, Description)
Doctor Specialist (Doctor Specialist)
Doctor versus Disease (Disease, Doctor_Specialist)
original_dataset (Symptom_1 to Symptom 17)
symptom_weights (Symptom, weight)

Analysis by SQL

1. Browse all the given disease with itching as symptom

In [15]:
```
query = '''
    select distinct Disease
    from
    original_dataset
    where
    Symptom_1 = 'itching' or
    Symptom_2 = 'itching' or
    Symptom_3 = 'itching' or
    Symptom_4 = 'itching' or
    Symptom_5 = 'itching' or
    Symptom_6 = 'itching' or
    Symptom_7 = 'itching' or
    Symptom_8 = 'itching' or
    Symptom_9 = 'itching' or
    Symptom_10 = 'itching' or
    Symptom_11 = 'itching' or
    Symptom_12 = 'itching' or
    Symptom_13 = 'itching' or
    Symptom_14 = 'itching' or
    Symptom_15 = 'itching' or
    Symptom_16 = 'itching' or
    Symptom_17 = 'itching'
'''
ps.sqldf(query)
```

Out[15]:

	Disease
0	Fungal infection
1	Chronic cholestasis
2	Drug Reaction
3	Jaundice
4	Chicken pox
5	Hepatitis B

2. Count how many patient suffering from corresponding syndrome in original dataset

In [16]:
```
query = '''
    with col1 as
    (
    select Symptom_1 as Symptom, count(Symptom_1) as counts
    from original_dataset
    group by
    Symptom_1
    )
    ,

    col2 as

    (
    select Symptom_2, count(Symptom_2) as counts
    from original_dataset
    group by
    Symptom_2
    )
    ,

    col3 as

    (
    select Symptom_3, count(Symptom_3) as counts
    from original_dataset
    group by
    Symptom_3
    )
    ,

    col4 as

    (
    select Symptom_4, count(Symptom_4) as counts
    from original_dataset
    group by
    Symptom_4
    )
    ,
    col5 as

    (
    select Symptom_5, count(Symptom_5) as counts
    from original_dataset
    group by
    Symptom_5
    )
    ,

    col6 as

    (
    select Symptom_6, count(Symptom_6) as counts
    from original_dataset
    group by
    Symptom_6
    )
    ,

    col7 as

    (
    select Symptom_7, count(Symptom_7) as counts
    from original_dataset
    group by
    Symptom_7
    )
    ,

    col8 as

    (
    select Symptom_8, count(Symptom_8) as counts
    from original_dataset
    group by
    Symptom_8
    )
    ,

    col9 as

    (
    select Symptom_9, count(Symptom_9) as counts
    from original_dataset
    group by
    Symptom_9
    )
    ,

    col10 as

    (
    select Symptom_10, count(Symptom_10) as counts
    from original_dataset
    group by
    Symptom_10
    )
    ,

    col11 as

    (
    select Symptom_11, count(Symptom_11) as counts
    from original_dataset
    group by
    Symptom_11
    )
    ,

    col12 as

    (
    select Symptom_12, count(Symptom_12) as counts
    from original_dataset
    group by
    Symptom_12
    )
    ,

    col13 as

    (
    select Symptom_13, count(Symptom_13) as counts
    from original_dataset
    group by
    Symptom_13
    )
    ,

    col14 as

    (
    select Symptom_14, count(Symptom_14) as counts
    from original_dataset
    group by
    Symptom_14
    )
    ,

    col15 as

    (
    select Symptom_15, count(Symptom_15) as counts
    from original_dataset
    group by
    Symptom_15
    )
    ,

    col16 as
```

```
    (
    select Symptom_16, count(Symptom_16) as counts
    from original_dataset
    group by
    Symptom_16
    )
    ,

    col17 as

    (
    select Symptom_17, count(Symptom_17) as counts
    from original_dataset
    group by
    Symptom_17
    )    -- DO EXECUTE the code once before adding a similar sub query !!!

    -- 1. THIS SUBQUERY IS TO COUNT THE SYMPTOM FOR EACH COLUMN, PLEASE ENSURE THAT

    select Symptom, sum(counts) as counts_all from  -- 3. THIS IS ACTUALLY THE LAST

    (select * from col1 union all
    select * from col2 union all
    select * from col3 union all
    select * from col4 union all
    select * from col5 union all
    select * from col6 union all
    select * from col7 union all
    select * from col8 union all
    select * from col9 union all
    select * from col10 union all
    select * from col11 union all
    select * from col12 union all
    select * from col13 union all
    select * from col14 union all
    select * from col15 union all
    select * from col16 union all
    select * from col17)

    -- 2. THIS IS TO UNION ALL THE DISEASE~COUNT PAIR INTO TWO COLUMN BEFORE AGGREG
    -- DO NOTE THAT WE MUST NOT DEDUPLICATE THE RECORD, ELSE SOME RECORD MAY GET LO

    group by Symptom
    order by counts_all desc

'''

ps.sqldf(query)



# p.s.: I have tried multiple times to approach each task before duplicating the si
# the code seems to be complicated though...

# do try to execute the code after add each column instead of doing it once for all
```

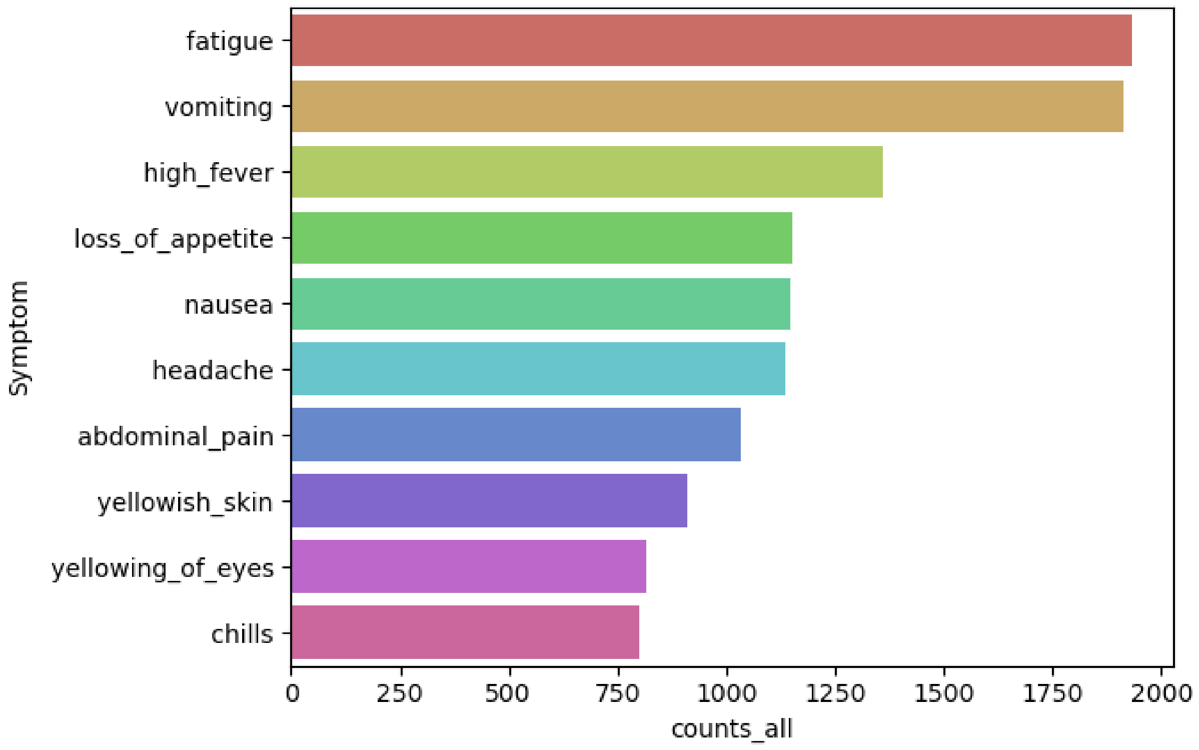
Out[16]:

	Symptom	counts_all
0	fatigue	1932
1	vomiting	1914
2	high_fever	1362
3	loss_of_appetite	1152
4	nausea	1146
...	...	...
127	dischromic _patches	108
128	dehydration	108
129	blackheads	108
130	foul_smell_of urine	102
131	None	0

132 rows × 2 columns

In [17]:
```
# visulize top 10 frequent symptoms
res = ps.sqldf(query)
sns.barplot(res.iloc[: 10, :], y = 'Symptom', x = 'counts_all', palette = 'hls')
```

Out[17]:
```
<Axes: xlabel='counts_all', ylabel='Symptom'>
```



It seems that most patient were suffering from fatigue, vomiting, high fever, apppetite lose, and nausea

This also implies the disadvantage of sql towards column-based dataset...tedius and duplicative subquereies, repetative union of aggregation, which prone to be errornous

3. If the patient is suffering from itching, which specialist will they probably visit?

```
In [18]: query = '''
    -- 1. select the possible disease with fatigue
    with diseases as
    (
    select distinct Disease
    from
    original_dataset
    where
    Symptom_1 = 'itching' or
    Symptom_2 = 'itching' or
    Symptom_3 = 'itching' or
    Symptom_4 = 'itching' or
    Symptom_5 = 'itching' or
    Symptom_6 = 'itching' or
    Symptom_7 = 'itching' or
    Symptom_8 = 'itching' or
    Symptom_9 = 'itching' or
    Symptom_10 = 'itching' or
    Symptom_11 = 'itching' or
    Symptom_12 = 'itching' or
    Symptom_13 = 'itching' or
    Symptom_14 = 'itching' or
    Symptom_15 = 'itching' or
    Symptom_16 = 'itching' or
    Symptom_17 = 'itching'
    )
    select distinct Doctor_Specialist
    from original_dataset
    full join
    doctor_versus_disease
    on
    original_dataset.Disease = doctor_versus_disease.Disease

    where
    original_dataset.Disease in
    (
    select Disease from diseases
    )

'''
ps.sqldf(query)
```

Out[18]:

	Doctor_Specialist
0	Dermatologist
1	Hepatologist
2	Allergist
3	Gastroenterologist
4	hepatologist

The patient suffering from itching would possibly go to the Dermatologist, Hepatologist, Allergist, Gastroenterologist, or hepatologist.

2. Data preprocessing

This is a **Column-based** dataset. Therefore, we shall convert them to list before undergoing further analysis.

This is also why querying is so tedious through SQL.

In [19]:
```
# set a new column, 'Symptoms', in the end
original_dataset['Symptoms'] = 0
original_dataset.head()
```

Out[19]:

	Disease	Symptom_1	Symptom_2	Symptom_3	Symptom_4	Symptom_5
0	Fungal infection	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	NaN
1	Fungal infection	skin_rash	nodal_skin_eruptions	dischromic _patches	NaN	NaN
2	Fungal infection	itching	nodal_skin_eruptions	dischromic _patches	NaN	NaN
3	Fungal infection	itching	skin_rash	dischromic _patches	NaN	NaN
4	Fungal infection	itching	skin_rash	nodal_skin_eruptions	NaN	NaN

In [20]:
```
# the new column, Symptoms shall store the list-based symptoms corresponding to dif

for i in range(original_dataset.shape[0]): # by N of row
    value = original_dataset.iloc[i].tolist() # transfer entire row into list
    original_dataset["Symptoms"][i] = value[1:18] # exclude title & last 0, only in
```

```
C:\Users\Raymo\AppData\Local\Temp\ipykernel_8708\2226175210.py:5: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  original_dataset["Symptoms"][i] = value[1:18] # exclude title & last 0, only inclu
de 17 symptoms in between
```

Warning!! once we add a column storing lists, pandasql would not work!!!

```
In [21]: original_dataset.head() # the last column consists of all the 17 symptoms
```

Out[21]:

	Disease	Symptom_1	Symptom_2	Symptom_3	Symptom_4	Symptom_5
0	Fungal infection	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	NaN
1	Fungal infection	skin_rash	nodal_skin_eruptions	dischromic _patches	NaN	NaN
2	Fungal infection	itching	nodal_skin_eruptions	dischromic _patches	NaN	NaN
3	Fungal infection	itching	skin_rash	dischromic _patches	NaN	NaN
4	Fungal infection	itching	skin_rash	nodal_skin_eruptions	NaN	NaN

```
In [22]: column_values = original_dataset[['Symptom_1', 'Symptom_2', 'Symptom_3', 'Symptom_4
                'Symptom_5', 'Symptom_6', 'Symptom_7', 'Symptom_8', 'Symptom_9',
                'Symptom_10', 'Symptom_11', 'Symptom_12', 'Symptom_13', 'Symptom_14',
                'Symptom_15', 'Symptom_16', 'Symptom_17']].values.ravel()  # change data the
```

```
In [23]: # count the total number of symptoms
         symps = pd.unique(column_values).tolist()
         # print(len(symps)) # 132, has a nan
         symps = [i for i in symps if str(i) != "nan"] # remove 'nan'

         print(len(symps))
```

```
131
```

`ravel data` -> `unique value` -> `tolist` -> `remove nan`

There are 131 symptoms here, identical to sql analysis that has been previously conducted

```
In [24]: new_data = symptoms = pd.DataFrame(columns = symps ,index = original_dataset.index)
         # this is done to set unique symptoms as column instead, while the row index is cor
         # and create two copies
```

In [25]:
```
new_data.head()
```

Out[25]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering	ch
0	NaN	NaN	NaN	NaN	NaN	NaN	N
1	NaN	NaN	NaN	NaN	NaN	NaN	N
2	NaN	NaN	NaN	NaN	NaN	NaN	N
3	NaN	NaN	NaN	NaN	NaN	NaN	N
4	NaN	NaN	NaN	NaN	NaN	NaN	N

In [26]:
```
new_data.tail()
```

Out[26]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering
4915	NaN	NaN	NaN	NaN	NaN	NaN
4916	NaN	NaN	NaN	NaN	NaN	NaN
4917	NaN	NaN	NaN	NaN	NaN	NaN
4918	NaN	NaN	NaN	NaN	NaN	NaN
4919	NaN	NaN	NaN	NaN	NaN	NaN

In [27]:
```
symptoms["Symptoms"] = original_dataset["Symptoms"]
```

The copy of `symptoms` is to store and fill the corresponding symptom into the column. By one-hot way

In [28]:
```
symptoms.head()
```

Out[28]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering	ch
0	NaN	NaN	NaN	NaN	NaN	NaN	N
1	NaN	NaN	NaN	NaN	NaN	NaN	N
2	NaN	NaN	NaN	NaN	NaN	NaN	N
3	NaN	NaN	NaN	NaN	NaN	NaN	N
4	NaN	NaN	NaN	NaN	NaN	NaN	N

In [29]:
```
for i in symps:
    symptoms[i] = symptoms.apply(lambda x:1 if i in x.Symptoms else 0, axis=1)  # f
```

In [30]:
```
symptoms.head()
```

Out[30]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering	ch
0	1	1	1	1	0	0	
1	0	1	1	1	0	0	
2	1	0	1	1	0	0	
3	1	1	0	1	0	0	
4	1	1	1	0	0	0	

In [31]:
```
symptoms["Disease"] = original_dataset["Disease"] # add a Disease column into sympt
symptoms = symptoms.drop("Symptoms",axis=1) # drop the original list-stored columns
symptoms.head()
```

Out[31]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering	ch
0	1	1	1	1	0	0	
1	0	1	1	1	0	0	
2	1	0	1	1	0	0	
3	1	1	0	1	0	0	
4	1	1	1	0	0	0	

In [43]:
```
# this query is to concatinate the corresponding physician into the one-hot-encoded
query = '''
    select * from
    symptoms
    full join
    doctor_versus_disease
    on
    symptoms.Disease = doctor_versus_disease.Disease

'''

analyze_data = ps.sqldf(query)
```

In [44]:
```
analyze_data.head()
```

Out[44]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering	ch
0	1	1	1	1	0	0	
1	0	1	1	1	0	0	
2	1	0	1	1	0	0	
3	1	1	0	1	0	0	
4	1	1	1	0	0	0	

In [48]:
```
analyze_data['Doctor_Specialist'].info() # every cell in Doctor_Specialist are unnu
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 4920 entries, 0 to 4919
Series name: Doctor_Specialist
Non-Null Count  Dtype
--------------  -----
4920 non-null   object
dtypes: object(1)
memory usage: 38.6+ KB
```

In [46]:
```
analyze_data.describe()
```

Out[46]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing
count	4920.000000	4920.000000	4920.000000	4920.000000	4920.000000
mean	0.137805	0.159756	0.021951	0.021951	0.045122
std	0.344730	0.366417	0.146539	0.146539	0.207593
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000

In [51]:
```
guidance = analyze_data.drop('Disease', axis = 1)
```

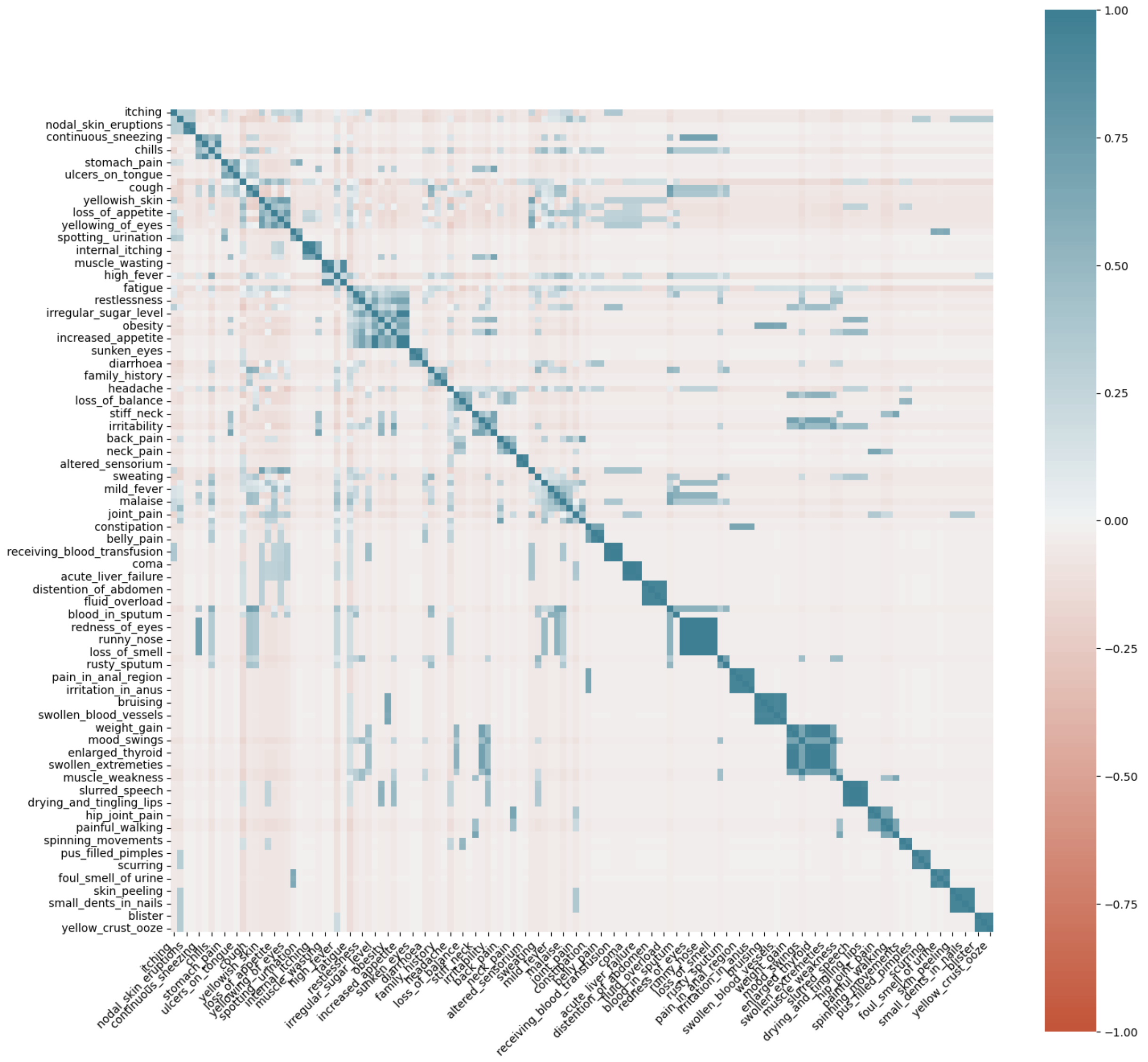
In [52]:
```
guidance.head()
```

Out[52]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering	ch
0	1	1	1	1	0	0	
1	0	1	1	1	0	0	
2	1	0	1	1	0	0	
3	1	1	0	1	0	0	
4	1	1	1	0	0	0	

In [62]:
```
# see correlations between symptoms
plt.figure(figsize = (16.5, 16.5))
corr = guidance.corr()
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True, annot = False
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right')
plt.show()
```

```
C:\Users\Raymo\AppData\Local\Temp\ipykernel_8708\1612129419.py:2: FutureWarning: The
default value of numeric_only in DataFrame.corr is deprecated. In a future version,
it will default to False. Select only valid columns or specify the value of numeric_
only to silence this warning.
  corr = guidance.corr()
```



Some Symptoms are closely correlated, medically

Model 1 Train the model for `inpatient guidance`

3. Model Training & Testing

The `guidance` dataset stores the symptoms corresponding to the physician that cope with such a disease

In [54]:
```
# Train-test split
x = guidance.drop('Doctor_Specialist', axis = 1)
y = guidance.Doctor_Specialist
```

In [64]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.1, random_sta
```

In [65]:
```
# Logistic Regression
classifier_logistic = LogisticRegression()

# K Nearest Neighbors
classifier_KNN = KNeighborsClassifier()

# Random Forest
classifier_RF = RandomForestClassifier()

# Support Vector Classification
classifier_SVC = SVC(probability=True)

# GB classifier
classifier_GB = GradientBoostingClassifier()

# Gaussian Naive Bayes
classifier_NB = GaussianNB()
```

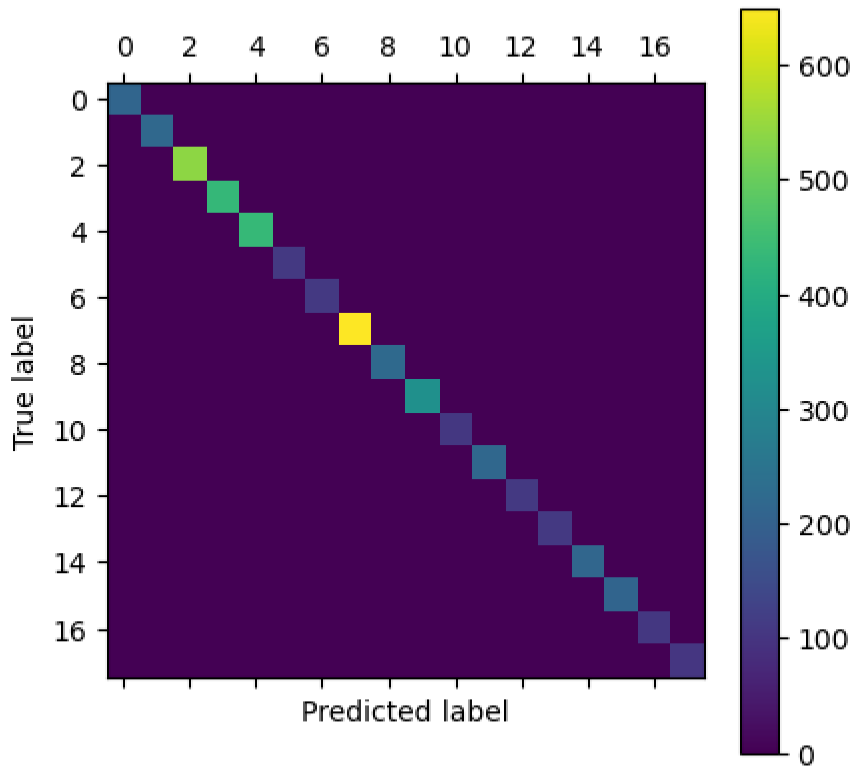
We shall use Logistic Regression, Random Forest Classifier, KNeighborsClassifier, SVC, GradientBoostingClassifier, and

Workflow:
`fit model` -> `predict result by training dataset` -> `cross validation` -> `get cross validation result` -> `plot confusion matrix`

Logistic Regression

In [71]:
```
classifier_logistic.fit(x_train, y_train)
y_predict = classifier_logistic.predict(x_train) # predict the result

scores = model_selection.cross_val_score(classifier_logistic, x_train, y_train, cv
print(f'For Logistic Regression, the accurracy is {round(scores.mean() * 100, 1)} +

# Confusion Matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For Logistic Regression, the accurracy is 100.0 +/- 0.0%
```



```
                     precision    recall  f1-score   support

          Allergist       1.00      1.00      1.00       211
       Cardiologist       1.00      1.00      1.00       219
      Dermatologist       1.00      1.00      1.00       539
    Endocrinologist       1.00      1.00      1.00       434
 Gastroenterologist       1.00      1.00      1.00       436
Gastroenterologist        1.00      1.00      1.00       109
       Gynecologist       1.00      1.00      1.00       108
       Hepatologist       1.00      1.00      1.00       650
   Internal Medcine       1.00      1.00      1.00       222
        Neurologist       1.00      1.00      1.00       327
        Osteopathic       1.00      1.00      1.00       106
   Otolaryngologist       1.00      1.00      1.00       217
       Pediatrician       1.00      1.00      1.00       108
       Phlebologist       1.00      1.00      1.00       108
      Pulmonologist       1.00      1.00      1.00       215
    Rheumatologists       1.00      1.00      1.00       210
       Tuberculosis       1.00      1.00      1.00       106
       hepatologist       1.00      1.00      1.00       103

           accuracy                           1.00      4428
          macro avg       1.00      1.00      1.00      4428
       weighted avg       1.00      1.00      1.00      4428
```

A logistic regressor could overkill this task...**Shall we continue to use a more complexed model?**

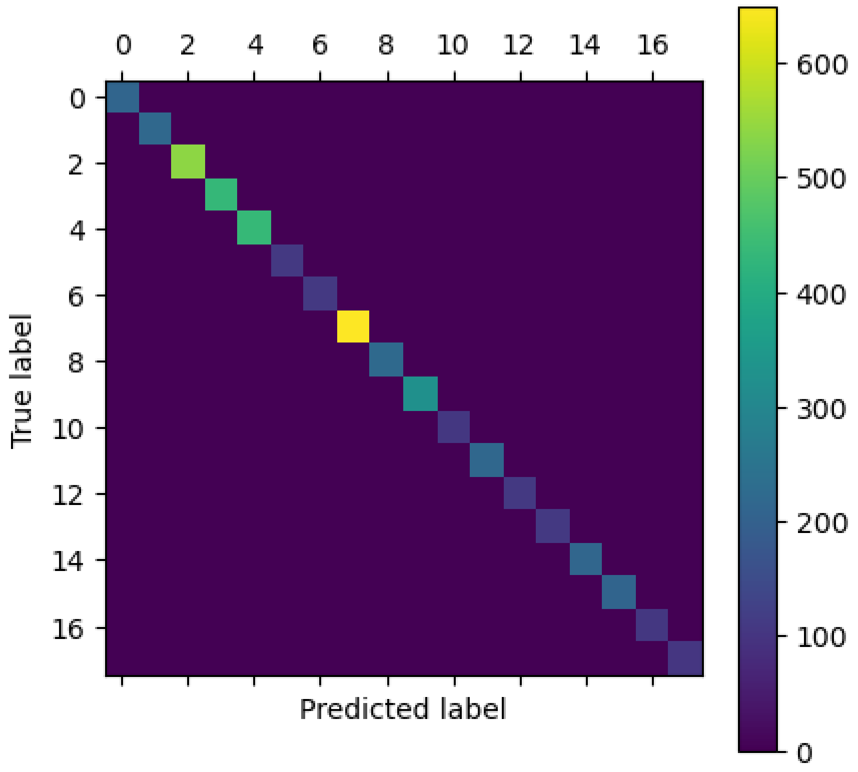
In principle, maybe we can just use a logistic regressor if its test result is also very ideal. But for **Etudie**, we also use other classifier instead

The following training and cross validation may for etudie purpose only

RandomForestClassifier

In [73]:
```
classifier_RF.fit(x_train, y_train)
y_predict = classifier_RF.predict(x_train) # predict the result

scores = model_selection.cross_val_score(classifier_RF, x_train, y_train, cv = 10)
print(f'For Random Forest, the accurracy is {round(scores.mean() * 100, 1)} +/- {ro

# Confusion Matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For Random Forest, the accurracy is 100.0 +/- 0.0%
```

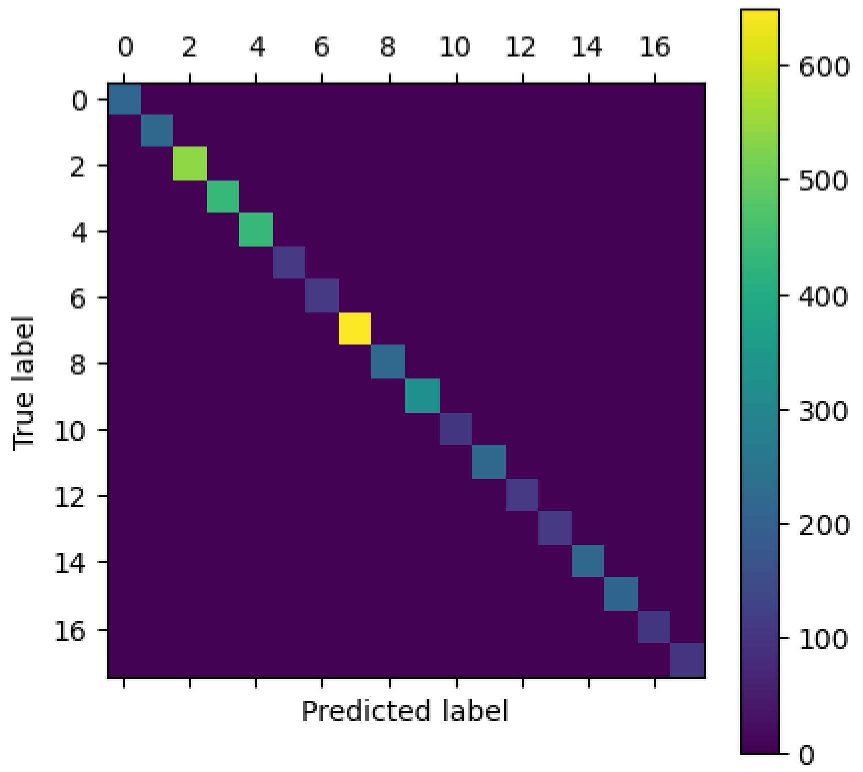


```
                      precision    recall  f1-score   support

           Allergist       1.00      1.00      1.00       211
        Cardiologist       1.00      1.00      1.00       219
       Dermatologist       1.00      1.00      1.00       539
     Endocrinologist       1.00      1.00      1.00       434
  Gastroenterologist       1.00      1.00      1.00       436
 Gastroenterologist        1.00      1.00      1.00       109
        Gynecologist       1.00      1.00      1.00       108
        Hepatologist       1.00      1.00      1.00       650
    Internal Medcine       1.00      1.00      1.00       222
         Neurologist       1.00      1.00      1.00       327
         Osteopathic       1.00      1.00      1.00       106
    Otolaryngologist       1.00      1.00      1.00       217
        Pediatrician       1.00      1.00      1.00       108
        Phlebologist       1.00      1.00      1.00       108
       Pulmonologist       1.00      1.00      1.00       215
     Rheumatologists       1.00      1.00      1.00       210
        Tuberculosis       1.00      1.00      1.00       106
        hepatologist       1.00      1.00      1.00       103

            accuracy                           1.00      4428
           macro avg       1.00      1.00      1.00      4428
        weighted avg       1.00      1.00      1.00      4428
```

KNeighborsClassifier

In [77]:
```
classifier_KNN.fit(x_train, y_train)
y_predict = classifier_KNN.predict(x_train)

scores = model_selection.cross_val_score(classifier_KNN, x_train, y_train, cv = 10)
print(f'For K-Neighbours Classifier, the accuracy is {round(scores.mean() * 100 ,2

# Confusion Matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For K-Neighbours Classifier, the accurracy is 100.0 +/- 0.0
```



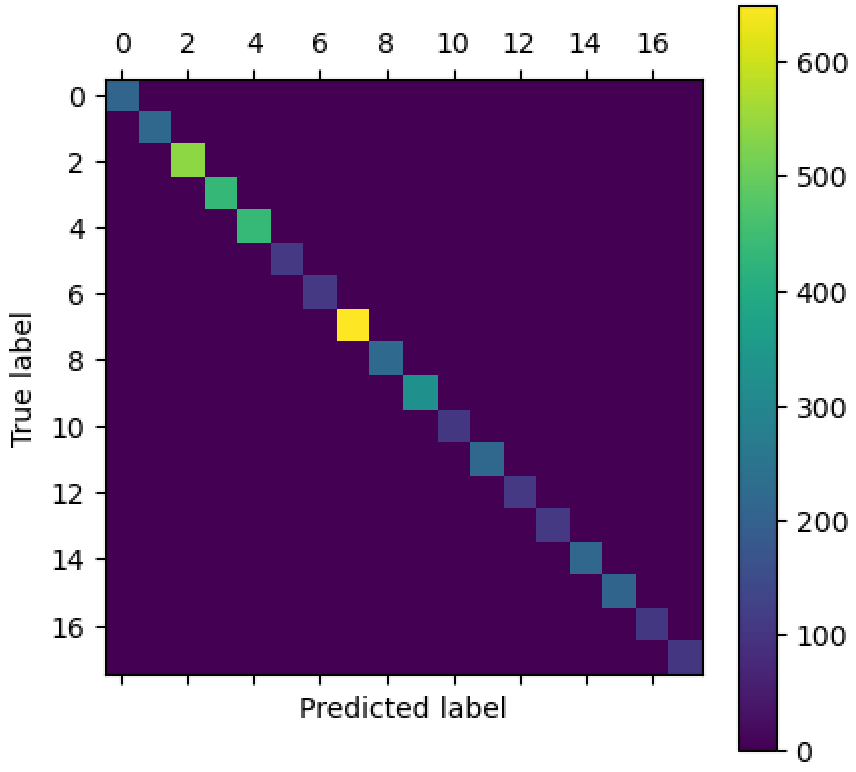
```
                      precision    recall  f1-score   support

          Allergist       1.00      1.00      1.00       211
       Cardiologist       1.00      1.00      1.00       219
     Dermatologist        1.00      1.00      1.00       539
    Endocrinologist       1.00      1.00      1.00       434
  Gastroenterologist      1.00      1.00      1.00       436
Gastroenterologist        1.00      1.00      1.00       109
       Gynecologist       1.00      1.00      1.00       108
       Hepatologist       1.00      1.00      1.00       650
    Internal Medcine      1.00      1.00      1.00       222
        Neurologist       1.00      1.00      1.00       327
        Osteopathic       1.00      1.00      1.00       106
    Otolaryngologist      1.00      1.00      1.00       217
       Pediatrician       1.00      1.00      1.00       108
       Phlebologist       1.00      1.00      1.00       108
     Pulmonologist        1.00      1.00      1.00       215
    Rheumatologists       1.00      1.00      1.00       210
       Tuberculosis       1.00      1.00      1.00       106
       hepatologist       1.00      1.00      1.00       103

           accuracy                           1.00      4428
          macro avg       1.00      1.00      1.00      4428
       weighted avg       1.00      1.00      1.00      4428
```

SVC

In [81]:
```
classifier_SVC.fit(x_train, y_train)
y_predict = classifier_SVC.predict(x_train)

# cross validation
```

```
scores = model_selection.cross_val_score(classifier_SVC, x_train, y_train, cv = 10)
print(f'For SVC, the classification accurracy is {round(scores.mean() * 100, 2)} +/

# confusion matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For SVC, the classification accurracy is 100.0 +/- 0.0
```



```
                       precision    recall  f1-score   support

          Allergist       1.00      1.00      1.00       211
        Cardiologist       1.00      1.00      1.00       219
       Dermatologist       1.00      1.00      1.00       539
     Endocrinologist       1.00      1.00      1.00       434
  Gastroenterologist       1.00      1.00      1.00       436
 Gastroenterologist        1.00      1.00      1.00       109
        Gynecologist       1.00      1.00      1.00       108
         Hepatologist       1.00      1.00      1.00       650
    Internal Medcine       1.00      1.00      1.00       222
         Neurologist       1.00      1.00      1.00       327
         Osteopathic       1.00      1.00      1.00       106
    Otolaryngologist       1.00      1.00      1.00       217
        Pediatrician       1.00      1.00      1.00       108
         Phlebologist       1.00      1.00      1.00       108
       Pulmonologist       1.00      1.00      1.00       215
     Rheumatologists       1.00      1.00      1.00       210
         Tuberculosis       1.00      1.00      1.00       106
         hepatologist       1.00      1.00      1.00       103

            accuracy                           1.00      4428
           macro avg       1.00      1.00      1.00      4428
        weighted avg       1.00      1.00      1.00      4428
```

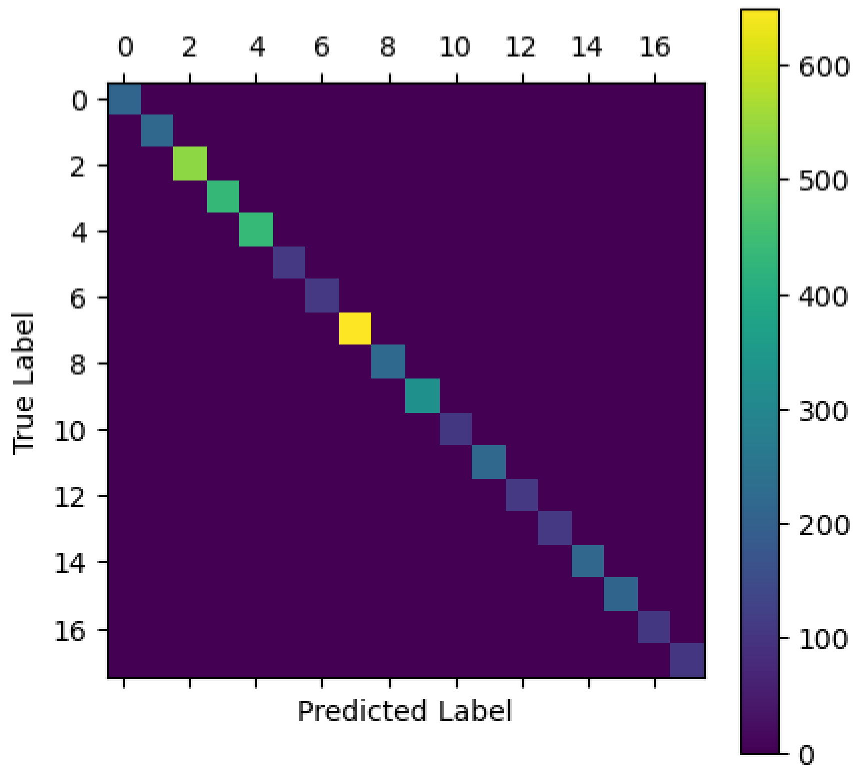
The model is a bit slow

GradientBoostingClassifier

In [84]:
```python
classifier_GB.fit(x_train, y_train)
y_predict = classifier_GB.predict(x_train)

# cross validation
scores = model_selection.cross_val_score(classifier_GB, x_train, y_train, cv = 10)

print(f'For Gradient Boosting Classifier, the accurracy is {round(scores.mean() * 1
    +/- {round(scores.std() * 1.96 / (10 ** 0.5), 2)}%')
```

```
For Gradient Boosting Classifier, the accurracy is 100.0    +/- 0.0%
```

In [107…
```python
# plotting confusing matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```



```
                      precision    recall  f1-score   support

          Allergist       1.00      1.00      1.00       211
       Cardiologist       1.00      1.00      1.00       219
      Dermatologist       1.00      1.00      1.00       539
    Endocrinologist       1.00      1.00      1.00       434
Gastroenterologist        1.00      1.00      1.00       436
Gastroenterologist       1.00      1.00      1.00       109
       Gynecologist       1.00      1.00      1.00       108
       Hepatologist       1.00      1.00      1.00       650
   Internal Medcine       1.00      1.00      1.00       222
         Neurologist      1.00      1.00      1.00       327
         Osteopathic      1.00      1.00      1.00       106
   Otolaryngologist       1.00      1.00      1.00       217
        Pediatrician      1.00      1.00      1.00       108
       Phlebologist       1.00      1.00      1.00       108
      Pulmonologist       1.00      1.00      1.00       215
    Rheumatologists       1.00      1.00      1.00       210
        Tuberculosis      1.00      1.00      1.00       106
       hepatologist       1.00      1.00      1.00       103

           accuracy                           1.00      4428
          macro avg       1.00      1.00      1.00      4428
       weighted avg       1.00      1.00      1.00      4428
```

This model is much slower...

GaussianNB

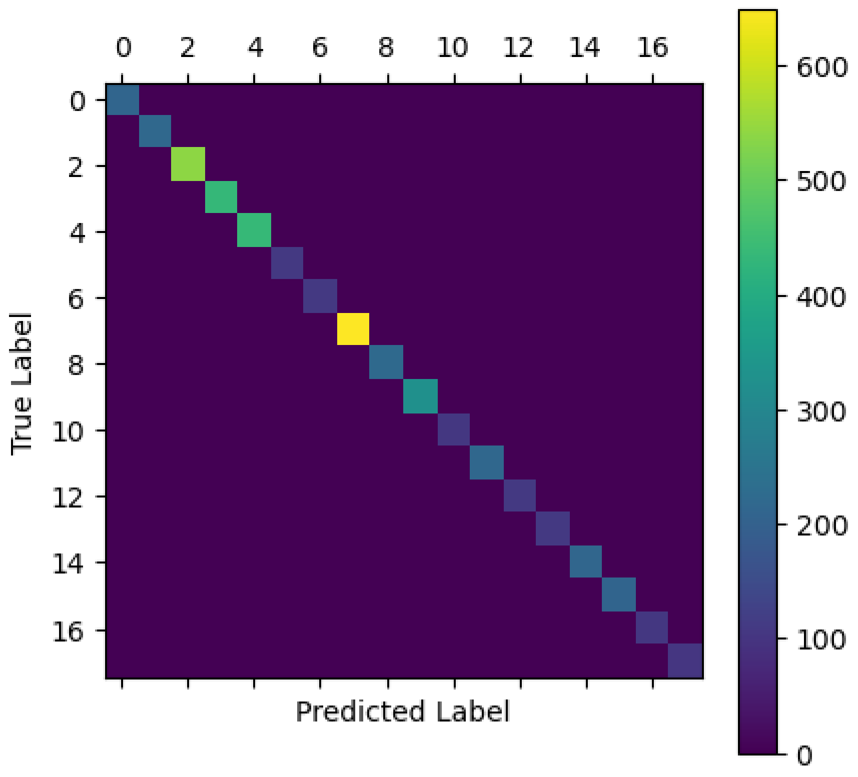
```
In [87]: classifier_NB.fit(x_train, y_train)
         y_predict = classifier_NB.predict(x_train)
```

```
# Cross Validation
scores = model_selection.cross_val_score(classifier_NB, x_train, y_train, cv = 10)
print(f'Fore Gaussian Naive Bayes Model, the accurracy is {round(scores.mean() * 10
```

```
Fore Gaussian Naive Bayes Model, the accurracy is 100.0 +/- 0.0
```

In [108…

```
# confusion matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
print(metrics.classification_report(y_train, y_predict))
```



```
                      precision    recall  f1-score   support

           Allergist       1.00      1.00      1.00       211
        Cardiologist       1.00      1.00      1.00       219
       Dermatologist       1.00      1.00      1.00       539
     Endocrinologist       1.00      1.00      1.00       434
  Gastroenterologist       1.00      1.00      1.00       436
 Gastroenterologist        1.00      1.00      1.00       109
        Gynecologist       1.00      1.00      1.00       108
        Hepatologist       1.00      1.00      1.00       650
    Internal Medcine       1.00      1.00      1.00       222
         Neurologist       1.00      1.00      1.00       327
         Osteopathic       1.00      1.00      1.00       106
    Otolaryngologist       1.00      1.00      1.00       217
        Pediatrician       1.00      1.00      1.00       108
        Phlebologist       1.00      1.00      1.00       108
       Pulmonologist       1.00      1.00      1.00       215
     Rheumatologists       1.00      1.00      1.00       210
        Tuberculosis       1.00      1.00      1.00       106
        hepatologist       1.00      1.00      1.00       103

            accuracy                           1.00      4428
           macro avg       1.00      1.00      1.00      4428
        weighted avg       1.00      1.00      1.00      4428
```

All of the models above, including logistic regression, are overfitted. Let's see what they perform in test model.

4. Model Evaluation

Precision(PPV, positive predictive value): tp / (tp + fp); High Precision means low fp

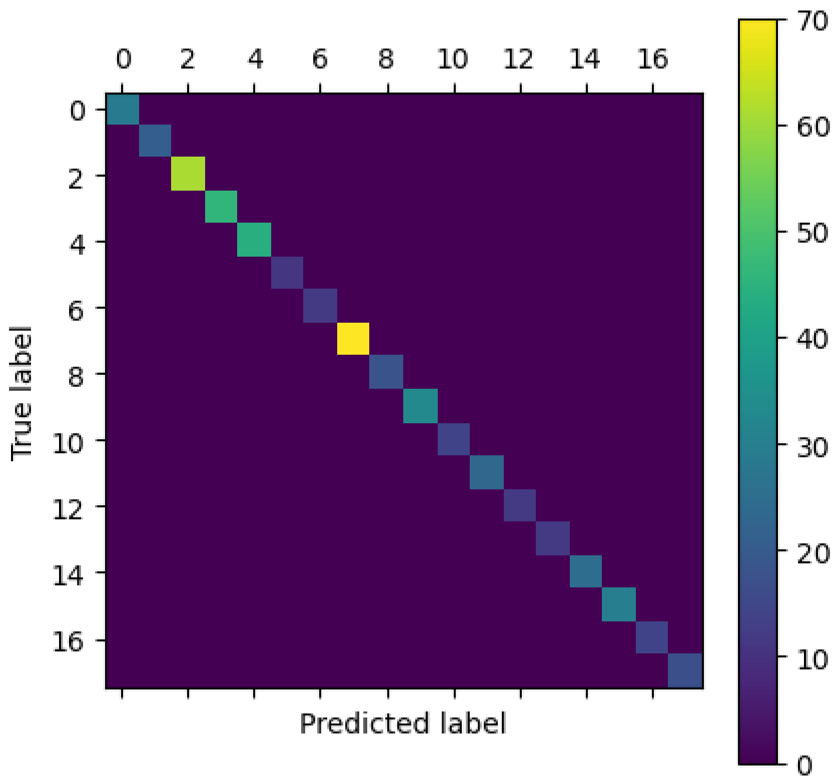
Recall(sensitivity, hit rate, true positive rate): tp / (tp + fn)

Accurracy: (tp + tn) / (tp + tn + fp + fn)

f1-Score: (2 * P * R) / (P + R)

1. Logistic Regression

In [97]:
```
y_final_predict = classifier_logistic.predict(x_test)

cm = metrics.confusion_matrix(y_test, y_final_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, y_final_predict))
```

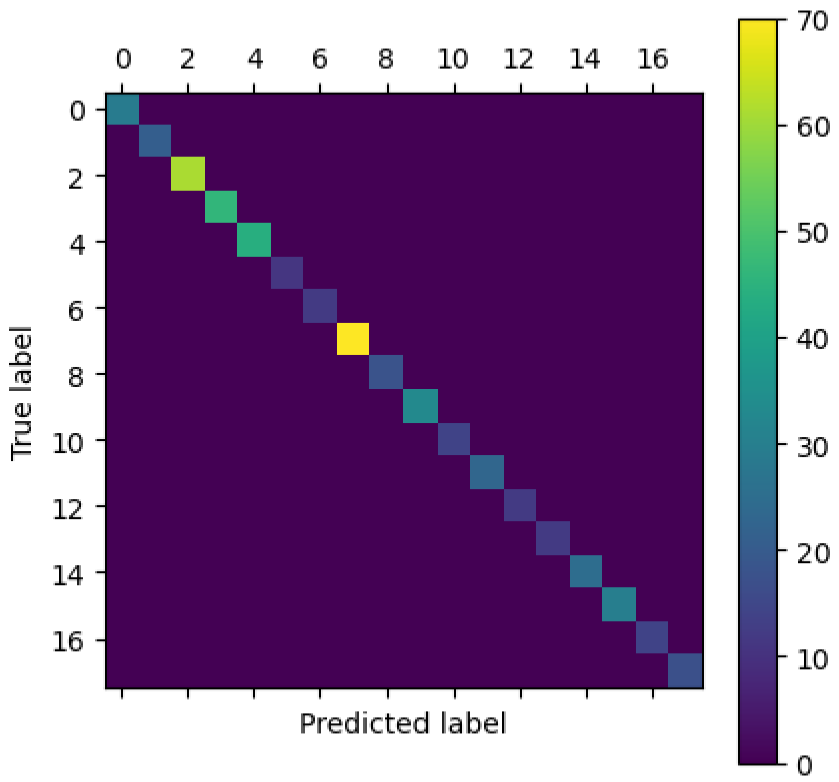


```
                      precision    recall  f1-score   support

           Allergist       1.00      1.00      1.00        29
        Cardiologist       1.00      1.00      1.00        21
       Dermatologist       1.00      1.00      1.00        61
     Endocrinologist       1.00      1.00      1.00        46
  Gastroenterologist       1.00      1.00      1.00        44
Gastroenterologist         1.00      1.00      1.00        11
        Gynecologist       1.00      1.00      1.00        12
         Hepatologist      1.00      1.00      1.00        70
     Internal Medcine      1.00      1.00      1.00        18
          Neurologist      1.00      1.00      1.00        33
          Osteopathic      1.00      1.00      1.00        14
     Otolaryngologist      1.00      1.00      1.00        23
         Pediatrician      1.00      1.00      1.00        12
         Phlebologist      1.00      1.00      1.00        12
        Pulmonologist      1.00      1.00      1.00        25
      Rheumatologists      1.00      1.00      1.00        30
         Tuberculosis      1.00      1.00      1.00        14
         hepatologist      1.00      1.00      1.00        17

             accuracy                          1.00       492
            macro avg      1.00      1.00      1.00       492
         weighted avg      1.00      1.00      1.00       492
```

If we only use patient symptom data for guidance to the corresponding department, a logistic regression might be enough...

2. RandomForestClassifier

```
In [100…
# Confusion Matrix
cm = metrics.confusion_matrix(y_test, classifier_RF.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, classifier_RF.predict(x_test)))
```

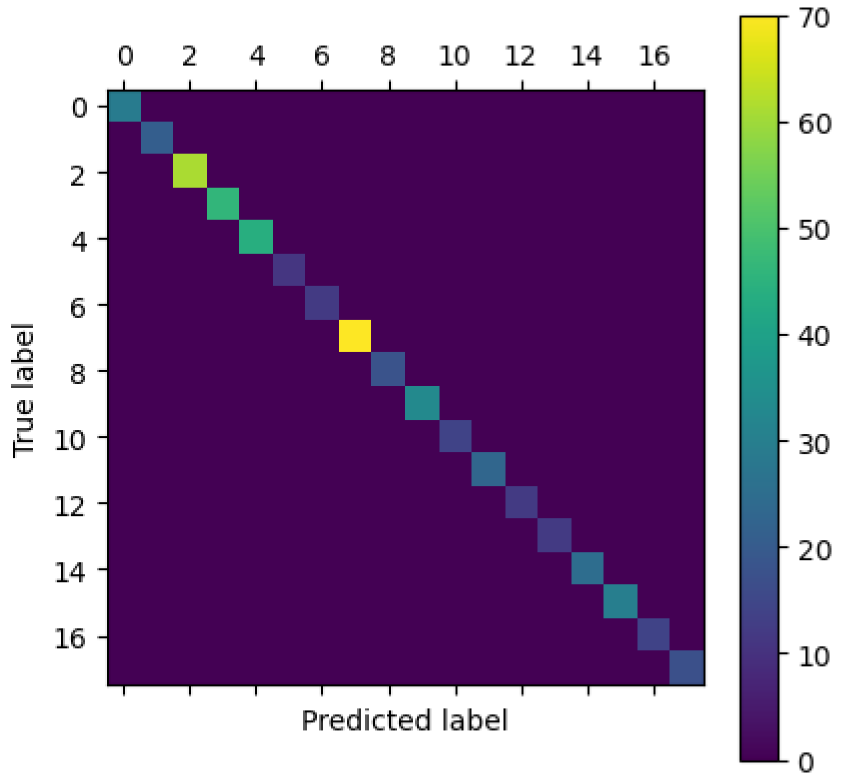


```
                      precision    recall  f1-score   support

           Allergist       1.00      1.00      1.00        29
        Cardiologist       1.00      1.00      1.00        21
       Dermatologist       1.00      1.00      1.00        61
     Endocrinologist       1.00      1.00      1.00        46
  Gastroenterologist       1.00      1.00      1.00        44
 Gastroenterologist        1.00      1.00      1.00        11
        Gynecologist       1.00      1.00      1.00        12
        Hepatologist       1.00      1.00      1.00        70
    Internal Medcine       1.00      1.00      1.00        18
         Neurologist       1.00      1.00      1.00        33
         Osteopathic       1.00      1.00      1.00        14
    Otolaryngologist       1.00      1.00      1.00        23
        Pediatrician       1.00      1.00      1.00        12
        Phlebologist       1.00      1.00      1.00        12
       Pulmonologist       1.00      1.00      1.00        25
     Rheumatologists       1.00      1.00      1.00        30
        Tuberculosis       1.00      1.00      1.00        14
        hepatologist       1.00      1.00      1.00        17

            accuracy                           1.00       492
           macro avg       1.00      1.00      1.00       492
        weighted avg       1.00      1.00      1.00       492
```

3. KNeighborsClassifier

In [102…

```
# Confusion Matrix
cm = metrics.confusion_matrix(y_test, classifier_KNN.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, classifier_KNN.predict(x_test)))
```

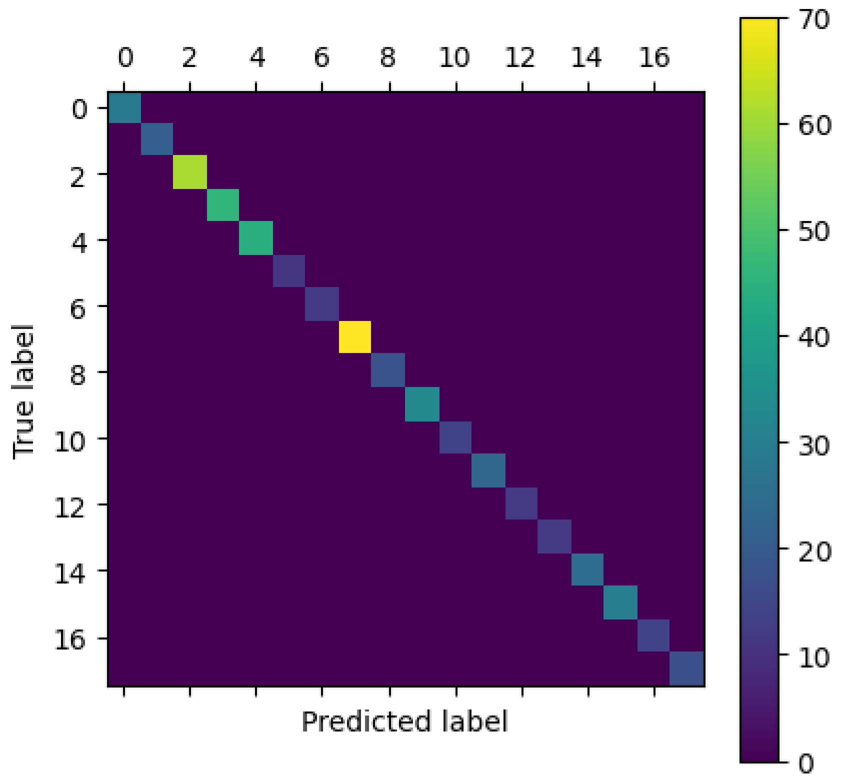


```
                     precision    recall  f1-score   support

          Allergist       1.00      1.00      1.00        29
       Cardiologist       1.00      1.00      1.00        21
      Dermatologist       1.00      1.00      1.00        61
    Endocrinologist       1.00      1.00      1.00        46
  Gastroenterologist      1.00      1.00      1.00        44
Gastroenterologist        1.00      1.00      1.00        11
       Gynecologist       1.00      1.00      1.00        12
       Hepatologist       1.00      1.00      1.00        70
    Internal Medcine      1.00      1.00      1.00        18
        Neurologist       1.00      1.00      1.00        33
        Osteopathic       1.00      1.00      1.00        14
   Otolaryngologist       1.00      1.00      1.00        23
       Pediatrician       1.00      1.00      1.00        12
       Phlebologist       1.00      1.00      1.00        12
      Pulmonologist       1.00      1.00      1.00        25
    Rheumatologists       1.00      1.00      1.00        30
       Tuberculosis       1.00      1.00      1.00        14
       hepatologist       1.00      1.00      1.00        17

           accuracy                           1.00       492
          macro avg       1.00      1.00      1.00       492
       weighted avg       1.00      1.00      1.00       492
```

4. SVC

In [106…

```
# confusion matrix
cm = metrics.confusion_matrix(y_test, classifier_SVC.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, classifier_SVC.predict(x_test)))
```

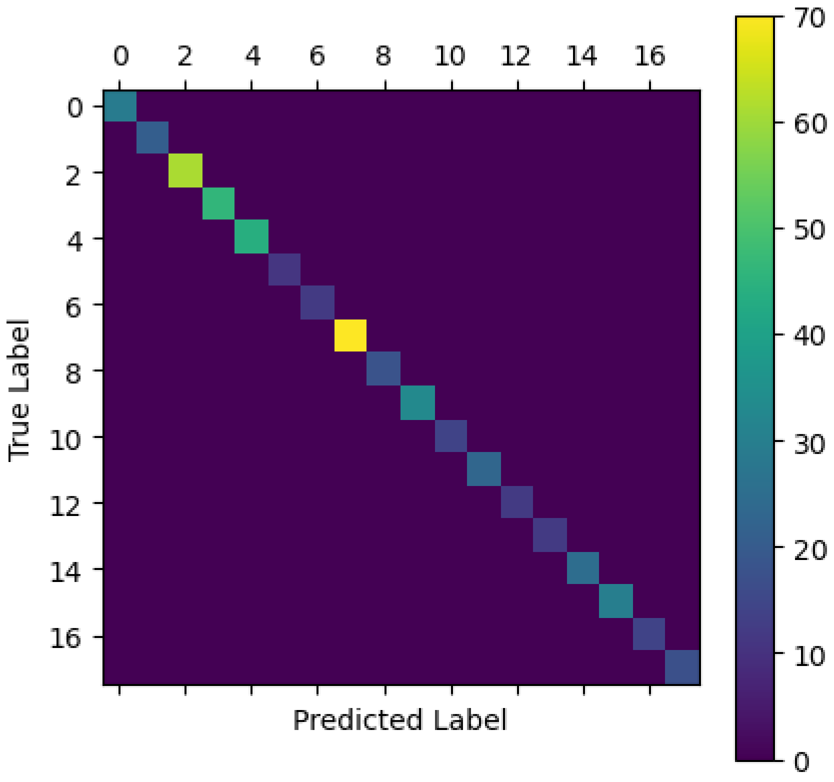


```
                      precision    recall  f1-score   support

           Allergist       1.00      1.00      1.00        29
        Cardiologist       1.00      1.00      1.00        21
       Dermatologist       1.00      1.00      1.00        61
     Endocrinologist       1.00      1.00      1.00        46
   Gastroenterologist      1.00      1.00      1.00        44
 Gastroenterologist        1.00      1.00      1.00        11
        Gynecologist       1.00      1.00      1.00        12
         Hepatologist      1.00      1.00      1.00        70
     Internal Medcine      1.00      1.00      1.00        18
          Neurologist      1.00      1.00      1.00        33
          Osteopathic      1.00      1.00      1.00        14
     Otolaryngologist      1.00      1.00      1.00        23
         Pediatrician      1.00      1.00      1.00        12
         Phlebologist      1.00      1.00      1.00        12
        Pulmonologist      1.00      1.00      1.00        25
     Rheumatologists       1.00      1.00      1.00        30
         Tuberculosis      1.00      1.00      1.00        14
         hepatologist      1.00      1.00      1.00        17

            accuracy                           1.00       492
           macro avg       1.00      1.00      1.00       492
        weighted avg       1.00      1.00      1.00       492
```

The model is a bit slow

5. GradientBoostingClassifier

```
In [111…
# plotting confusing matrix
cm = metrics.confusion_matrix(y_test, classifier_GB.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

print(metrics.classification_report(y_test, classifier_GB.predict(x_test)))
```

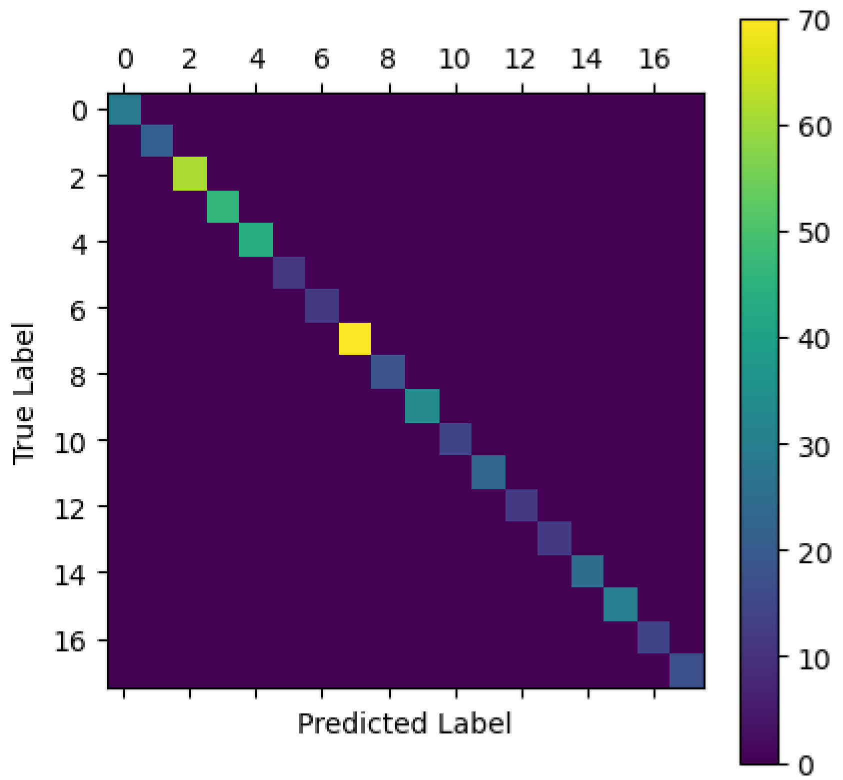


```
                     precision    recall  f1-score   support

          Allergist       1.00      1.00      1.00        29
       Cardiologist       1.00      1.00      1.00        21
      Dermatologist       1.00      1.00      1.00        61
    Endocrinologist       1.00      1.00      1.00        46
 Gastroenterologist       1.00      1.00      1.00        44
Gastroenterologist        1.00      1.00      1.00        11
       Gynecologist       1.00      1.00      1.00        12
       Hepatologist       1.00      1.00      1.00        70
   Internal Medcine       1.00      1.00      1.00        18
        Neurologist       1.00      1.00      1.00        33
        Osteopathic       1.00      1.00      1.00        14
   Otolaryngologist       1.00      1.00      1.00        23
       Pediatrician       1.00      1.00      1.00        12
       Phlebologist       1.00      1.00      1.00        12
      Pulmonologist       1.00      1.00      1.00        25
    Rheumatologists       1.00      1.00      1.00        30
       Tuberculosis       1.00      1.00      1.00        14
       hepatologist       1.00      1.00      1.00        17

           accuracy                           1.00       492
          macro avg       1.00      1.00      1.00       492
       weighted avg       1.00      1.00      1.00       492
```

This model is much slower...

GaussianNB

In [112…
```
# confusion matrix
cm = metrics.confusion_matrix(y_test, classifier_NB.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
print(metrics.classification_report(y_test, classifier_NB.predict(x_test)))
```



```
                      precision    recall  f1-score   support

           Allergist       1.00      1.00      1.00        29
        Cardiologist       1.00      1.00      1.00        21
       Dermatologist       1.00      1.00      1.00        61
     Endocrinologist       1.00      1.00      1.00        46
  Gastroenterologist       1.00      1.00      1.00        44
Gastroenterologist         1.00      1.00      1.00        11
        Gynecologist       1.00      1.00      1.00        12
         Hepatologist      1.00      1.00      1.00        70
     Internal Medcine      1.00      1.00      1.00        18
          Neurologist      1.00      1.00      1.00        33
          Osteopathic      1.00      1.00      1.00        14
    Otolaryngologist       1.00      1.00      1.00        23
        Pediatrician       1.00      1.00      1.00        12
        Phlebologist       1.00      1.00      1.00        12
       Pulmonologist       1.00      1.00      1.00        25
     Rheumatologists       1.00      1.00      1.00        30
         Tuberculosis      1.00      1.00      1.00        14
        hepatologist       1.00      1.00      1.00        17

            accuracy                           1.00       492
           macro avg       1.00      1.00      1.00       492
        weighted avg       1.00      1.00      1.00       492
```

All of the models above, including logistic regression, are overfitted, even in testing data.

Therefore, if we have to figure out which one is the best, maybe the only answer would be the **logistic regression** model

Feature Importance

In [119…

```
importances = classifier_RF.feature_importances_

indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature importance ranking by RF:")
for ind in range(x.shape[1]):
  print ("{0} : {1}".format(x.columns[indices[ind]],round(importances[indices[ind]]
Feature importance ranking by RF:
 skin_rash : 0.0585
 nausea : 0.0365
 yellowing_of_eyes : 0.0358
 vomiting : 0.0301
 yellowish_skin : 0.0282
 headache : 0.0247
 abdominal_pain : 0.0239
 breathlessness : 0.0228
 swelling_joints : 0.0225
 fatigue : 0.0205
 chills : 0.0204
 chest_pain : 0.0195
 loss_of_appetite : 0.0188
 cough : 0.0187
 painful_walking : 0.0185
 high_fever : 0.0169
 irritability : 0.0169
 excessive_hunger : 0.0168
 muscle_pain : 0.0168
 stomach_pain : 0.0151
 sweating : 0.0139
 burning_micturition : 0.0137
 loss_of_balance : 0.0121
 weight_loss : 0.011
 bladder_discomfort : 0.0108
 malaise : 0.0106
itching : 0.0105
 spotting_ urination : 0.0105
 abnormal_menstruation : 0.0104
 constipation : 0.01
 lethargy : 0.0096
 back_pain : 0.0094
 dark_urine : 0.009
 lack_of_concentration : 0.009
 restlessness : 0.009
 continuous_feel_of_urine : 0.0079
 weakness_of_one_body_side : 0.0078
 patches_in_throat : 0.0075
 altered_sensorium : 0.0074
 neck_pain : 0.0073
 extra_marital_contacts : 0.0072
 continuous_sneezing : 0.0072
 diarrhoea : 0.0072
 watering_from_eyes : 0.0071
 unsteadiness : 0.0069
 pain_in_anal_region : 0.0068
 receiving_blood_transfusion : 0.0067
 mood_swings : 0.0067
 bloody_stool : 0.0066
 muscle_wasting : 0.0065
 spinning_movements : 0.0062
 prominent_veins_on_calf : 0.0062
 pain_behind_the_eyes : 0.0059
 shivering : 0.0058
 yellow_urine : 0.0057
```

```
swelled_lymph_nodes : 0.0057
indigestion : 0.0056
obesity : 0.0056
pain_during_bowel_movements : 0.0054
blurred_and_distorted_vision : 0.0054
blood_in_sputum : 0.0053
acidity : 0.0053
dizziness : 0.0053
joint_pain : 0.0053
history_of_alcohol_consumption : 0.0052
belly_pain : 0.0052
cramps : 0.0051
internal_itching : 0.0051
bruising : 0.005
toxic_look_(typhos) : 0.0049
irritation_in_anus : 0.0049
receiving_unsterile_injections : 0.0048
sunken_eyes : 0.0047
sinus_pressure : 0.0045
distention_of_abdomen : 0.0044
phlegm : 0.0043
swollen_legs : 0.0043
runny_nose : 0.004
fluid_overload : 0.0039
mild_fever : 0.0039
congestion : 0.0039
weakness_in_limbs : 0.0037
stiff_neck : 0.0037
visual_disturbances : 0.0036
dehydration : 0.0036
family_history : 0.0035
redness_of_eyes : 0.0035
passage_of_gases : 0.0033
mucoid_sputum : 0.0033
swelling_of_stomach : 0.0033
foul_smell_of urine : 0.0032
depression : 0.0031
slurred_speech : 0.0029
swollen_blood_vessels : 0.0028
ulcers_on_tongue : 0.0028
red_spots_over_body : 0.0028
hip_joint_pain : 0.0027
loss_of_smell : 0.0023
dischromic _patches : 0.0022
rusty_sputum : 0.0022
fast_heart_rate : 0.0021
nodal_skin_eruptions : 0.002
brittle_nails : 0.0018
movement_stiffness : 0.0018
polyuria : 0.0018
drying_and_tingling_lips : 0.0017
muscle_weakness : 0.0017
palpitations : 0.0016
knee_pain : 0.0015
increased_appetite : 0.0014
silver_like_dusting : 0.0013
```

```
yellow_crust_ooze : 0.0013
throat_irritation : 0.0013
irregular_sugar_level : 0.0012
weight_gain : 0.0011
anxiety : 0.0011
swollen_extremeties : 0.0011
small_dents_in_nails : 0.0011
red_sore_around_nose : 0.001
scurring : 0.001
enlarged_thyroid : 0.001
cold_hands_and_feets : 0.0009
blister : 0.0009
pus_filled_pimples : 0.0008
blackheads : 0.0008
acute_liver_failure : 0.0007
inflammatory_nails : 0.0007
stomach_bleeding : 0.0006
puffy_face_and_eyes : 0.0006
coma : 0.0006
skin_peeling : 0.0006
```

5. Insigits & Conclusion

1. It seems that logistic regression is enough to guide the patient to the corresponding physician. However, the usability of this model is still needed to be furtherly verified.
2. Common symptoms, like fatigue, vomiting, headache, abdominal pain generally more decisive on which department we should go.

Model 2 Train the model for `Disease Diagnosis`

3. Model Training & Testing

The `symptoms` dataset stores the symptoms corresponding to disease

In [135…
```
symptoms.head()
```

Out[135]:

	itching	skin_rash	nodal_skin_eruptions	dischromic _patches	continuous_sneezing	shivering	ch
0	1	1	1	1	0	0	
1	0	1	1	1	0	0	
2	1	0	1	1	0	0	
3	1	1	0	1	0	0	
4	1	1	1	0	0	0	

In [138…
```
# Train-test split
x = symptoms.drop('Disease', axis = 1)
y = symptoms.Disease
```

In [139…
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.1, random_sta
```

In [140…
```
# Logistic Regression
classifier_logistic = LogisticRegression()

# K Nearest Neighbors
classifier_KNN = KNeighborsClassifier()

# Random Forest
classifier_RF = RandomForestClassifier()

# Support Vector Classification
classifier_SVC = SVC(probability=True)

# GB classifier
classifier_GB = GradientBoostingClassifier()

# Gaussian Naive Bayes
classifier_NB = GaussianNB()
```

We shall use Logistic Regression, Random Forest Classifier, KNeighborsClassifier, SVC, GradientBoostingClassifier, and

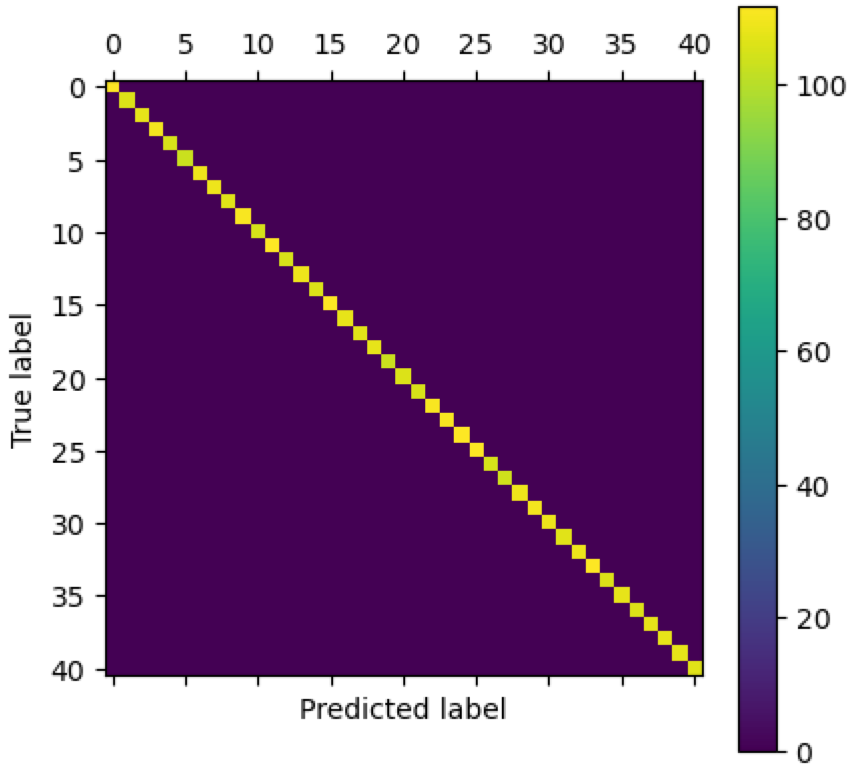
Workflow:
`fit model` -> `predict result by training dataset` -> `cross validation` -> `get cross validation result` -> `plot confusion matrix`

Logistic Regression

In [141…
```
classifier_logistic.fit(x_train, y_train)
y_predict = classifier_logistic.predict(x_train) # predict the result
```

```
scores = model_selection.cross_val_score(classifier_logistic, x_train, y_train, cv
print(f'For Logistic Regression, the accurracy is {round(scores.mean() * 100, 1)} +

# Confusion Matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For Logistic Regression, the accurracy is 100.0 +/- 0.0%
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00       112
                                   AIDS       1.00      1.00      1.00       106
                                   Acne       1.00      1.00      1.00       108
                    Alcoholic hepatitis       1.00      1.00      1.00       110
                                Allergy       1.00      1.00      1.00       105
                              Arthritis       1.00      1.00      1.00       103
                       Bronchial Asthma       1.00      1.00      1.00       109
                   Cervical spondylosis       1.00      1.00      1.00       109
                            Chicken pox       1.00      1.00      1.00       107
                    Chronic cholestasis       1.00      1.00      1.00       111
                            Common Cold       1.00      1.00      1.00       105
                                 Dengue       1.00      1.00      1.00       112
                              Diabetes        1.00      1.00      1.00       105
        Dimorphic hemmorhoids(piles)          1.00      1.00      1.00       109
                          Drug Reaction       1.00      1.00      1.00       106
                       Fungal infection       1.00      1.00      1.00       112
                                   GERD       1.00      1.00      1.00       108
                        Gastroenteritis       1.00      1.00      1.00       107
                           Heart attack       1.00      1.00      1.00       108
                            Hepatitis B       1.00      1.00      1.00       103
                            Hepatitis C       1.00      1.00      1.00       106
                            Hepatitis D       1.00      1.00      1.00       105
                            Hepatitis E       1.00      1.00      1.00       111
                          Hypertension        1.00      1.00      1.00       111
                        Hyperthyroidism       1.00      1.00      1.00       112
                           Hypoglycemia       1.00      1.00      1.00       112
                         Hypothyroidism       1.00      1.00      1.00       105
                               Impetigo       1.00      1.00      1.00       104
                               Jaundice       1.00      1.00      1.00       109
                                Malaria       1.00      1.00      1.00       110
                               Migraine       1.00      1.00      1.00       109
                        Osteoarthristis       1.00      1.00      1.00       107
             Paralysis (brain hemorrhage)     1.00      1.00      1.00       109
                    Peptic ulcer diseae       1.00      1.00      1.00       112
                              Pneumonia       1.00      1.00      1.00       106
                              Psoriasis       1.00      1.00      1.00       108
                           Tuberculosis       1.00      1.00      1.00       106
                                Typhoid       1.00      1.00      1.00       108
                Urinary tract infection       1.00      1.00      1.00       108
                         Varicose veins       1.00      1.00      1.00       108
                            hepatitis A       1.00      1.00      1.00       107

                               accuracy                           1.00      4428
                              macro avg       1.00      1.00      1.00      4428
                           weighted avg       1.00      1.00      1.00      4428
```

A logistic regressor could overkill this task...**Shall we continue to use a more complexed model?**

In principle, maybe we can just use a logistic regressor if its test result is also very ideal. But for **Etudie**, we also use other classifier instead

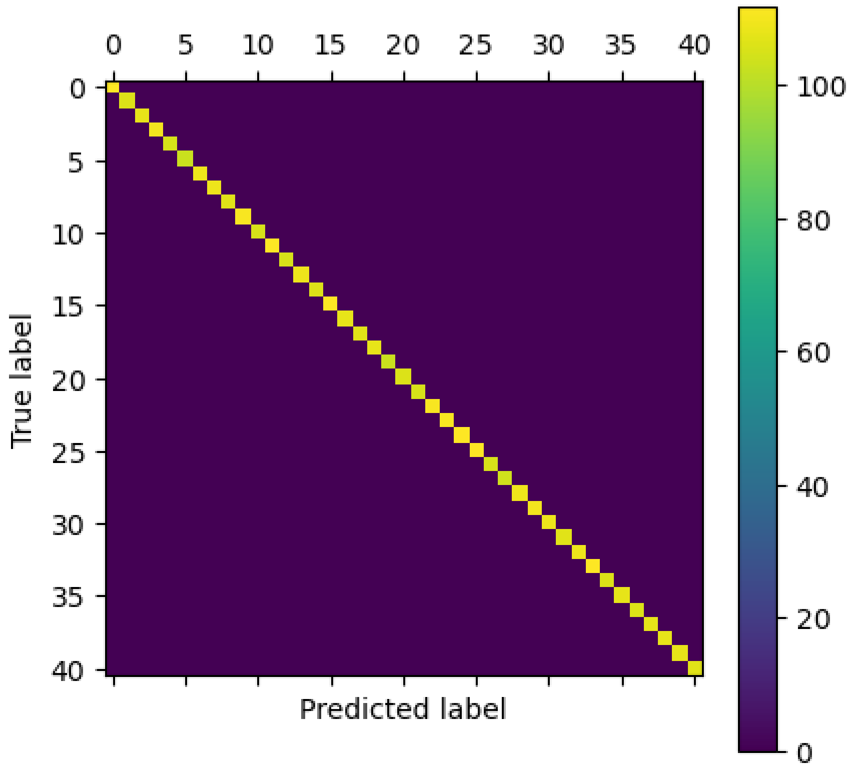
The following training and cross validation may for etudie purpose only

RandomForestClassifier

In [142…

```python
classifier_RF.fit(x_train, y_train)
y_predict = classifier_RF.predict(x_train) # predict the result

scores = model_selection.cross_val_score(classifier_RF, x_train, y_train, cv = 10)
print(f'For Random Forest, the accurracy is {round(scores.mean() * 100, 1)} +/- {ro

# Confusion Matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For Random Forest, the accurracy is 100.0 +/- 0.0%
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00       112
                                   AIDS       1.00      1.00      1.00       106
                                   Acne       1.00      1.00      1.00       108
                    Alcoholic hepatitis       1.00      1.00      1.00       110
                                Allergy       1.00      1.00      1.00       105
                              Arthritis       1.00      1.00      1.00       103
                       Bronchial Asthma       1.00      1.00      1.00       109
                   Cervical spondylosis       1.00      1.00      1.00       109
                            Chicken pox       1.00      1.00      1.00       107
                    Chronic cholestasis       1.00      1.00      1.00       111
                            Common Cold       1.00      1.00      1.00       105
                                 Dengue       1.00      1.00      1.00       112
                              Diabetes        1.00      1.00      1.00       105
        Dimorphic hemmorhoids(piles)       1.00      1.00      1.00       109
                          Drug Reaction       1.00      1.00      1.00       106
                       Fungal infection       1.00      1.00      1.00       112
                                   GERD       1.00      1.00      1.00       108
                        Gastroenteritis       1.00      1.00      1.00       107
                           Heart attack       1.00      1.00      1.00       108
                            Hepatitis B       1.00      1.00      1.00       103
                            Hepatitis C       1.00      1.00      1.00       106
                            Hepatitis D       1.00      1.00      1.00       105
                            Hepatitis E       1.00      1.00      1.00       111
                          Hypertension        1.00      1.00      1.00       111
                        Hyperthyroidism       1.00      1.00      1.00       112
                           Hypoglycemia       1.00      1.00      1.00       112
                         Hypothyroidism       1.00      1.00      1.00       105
                               Impetigo       1.00      1.00      1.00       104
                               Jaundice       1.00      1.00      1.00       109
                                Malaria       1.00      1.00      1.00       110
                               Migraine       1.00      1.00      1.00       109
                        Osteoarthristis       1.00      1.00      1.00       107
           Paralysis (brain hemorrhage)       1.00      1.00      1.00       109
                    Peptic ulcer diseae       1.00      1.00      1.00       112
                              Pneumonia       1.00      1.00      1.00       106
                              Psoriasis       1.00      1.00      1.00       108
                           Tuberculosis       1.00      1.00      1.00       106
                                Typhoid       1.00      1.00      1.00       108
                Urinary tract infection       1.00      1.00      1.00       108
                         Varicose veins       1.00      1.00      1.00       108
                            hepatitis A       1.00      1.00      1.00       107

                               accuracy                           1.00      4428
                              macro avg       1.00      1.00      1.00      4428
                           weighted avg       1.00      1.00      1.00      4428
```

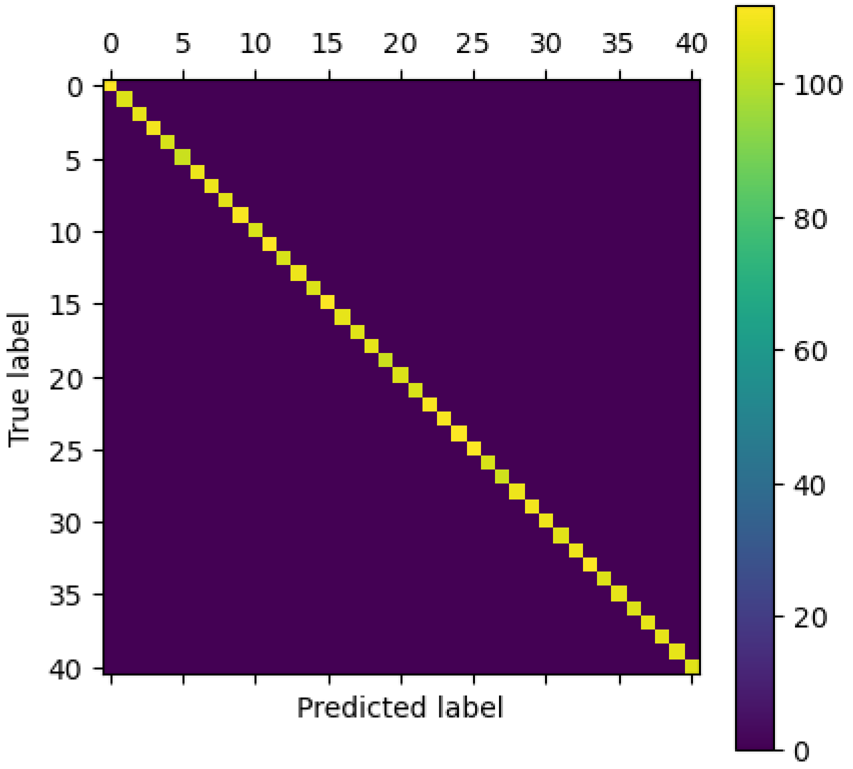
KNeighborsClassifier

In [143…

```
classifier_KNN.fit(x_train, y_train)
y_predict = classifier_KNN.predict(x_train)

scores = model_selection.cross_val_score(classifier_KNN, x_train, y_train, cv = 10)
print(f'For K-Neighbours Classifier, the accurracy is {round(scores.mean() * 100 ,2
```

```python
# Confusion Matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For K-Neighbours Classifier, the accurracy is 100.0 +/- 0.0
```



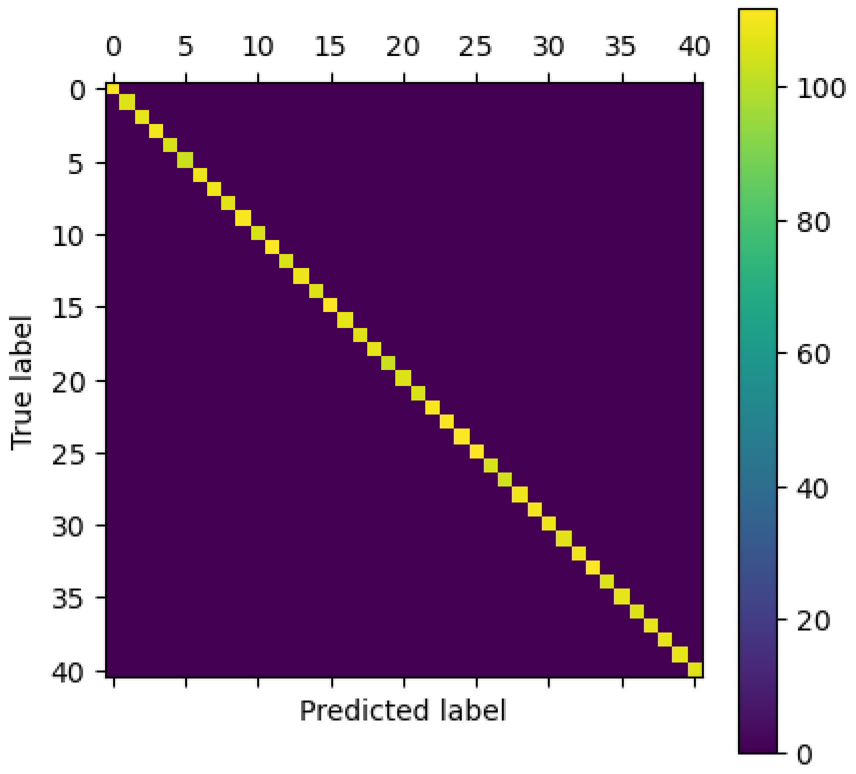
```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00       112
                                   AIDS       1.00      1.00      1.00       106
                                   Acne       1.00      1.00      1.00       108
                    Alcoholic hepatitis       1.00      1.00      1.00       110
                                Allergy       1.00      1.00      1.00       105
                              Arthritis       1.00      1.00      1.00       103
                       Bronchial Asthma       1.00      1.00      1.00       109
                   Cervical spondylosis       1.00      1.00      1.00       109
                            Chicken pox       1.00      1.00      1.00       107
                    Chronic cholestasis       1.00      1.00      1.00       111
                            Common Cold       1.00      1.00      1.00       105
                                 Dengue       1.00      1.00      1.00       112
                              Diabetes        1.00      1.00      1.00       105
        Dimorphic hemmorhoids(piles)          1.00      1.00      1.00       109
                          Drug Reaction       1.00      1.00      1.00       106
                       Fungal infection       1.00      1.00      1.00       112
                                   GERD       1.00      1.00      1.00       108
                        Gastroenteritis       1.00      1.00      1.00       107
                           Heart attack       1.00      1.00      1.00       108
                            Hepatitis B       1.00      1.00      1.00       103
                            Hepatitis C       1.00      1.00      1.00       106
                            Hepatitis D       1.00      1.00      1.00       105
                            Hepatitis E       1.00      1.00      1.00       111
                          Hypertension        1.00      1.00      1.00       111
                      Hyperthyroidism         1.00      1.00      1.00       112
                           Hypoglycemia       1.00      1.00      1.00       112
                         Hypothyroidism       1.00      1.00      1.00       105
                               Impetigo       1.00      1.00      1.00       104
                               Jaundice       1.00      1.00      1.00       109
                                Malaria       1.00      1.00      1.00       110
                               Migraine       1.00      1.00      1.00       109
                        Osteoarthristis       1.00      1.00      1.00       107
             Paralysis (brain hemorrhage)     1.00      1.00      1.00       109
                    Peptic ulcer diseae       1.00      1.00      1.00       112
                              Pneumonia       1.00      1.00      1.00       106
                              Psoriasis       1.00      1.00      1.00       108
                           Tuberculosis       1.00      1.00      1.00       106
                                Typhoid       1.00      1.00      1.00       108
                Urinary tract infection       1.00      1.00      1.00       108
                         Varicose veins       1.00      1.00      1.00       108
                            hepatitis A       1.00      1.00      1.00       107

                               accuracy                           1.00      4428
                              macro avg       1.00      1.00      1.00      4428
                           weighted avg       1.00      1.00      1.00      4428
```

SVC

In [144…
```
classifier_SVC.fit(x_train, y_train)
y_predict = classifier_SVC.predict(x_train)

# cross validation
scores = model_selection.cross_val_score(classifier_SVC, x_train, y_train, cv = 10)
```

```
print(f'For SVC, the classification accurracy is {round(scores.mean() * 100, 2)} +/

# confusion matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```

```
For SVC, the classification accurracy is 100.0 +/- 0.0
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00       112
                                   AIDS       1.00      1.00      1.00       106
                                   Acne       1.00      1.00      1.00       108
                    Alcoholic hepatitis       1.00      1.00      1.00       110
                                Allergy       1.00      1.00      1.00       105
                              Arthritis       1.00      1.00      1.00       103
                       Bronchial Asthma       1.00      1.00      1.00       109
                   Cervical spondylosis       1.00      1.00      1.00       109
                            Chicken pox       1.00      1.00      1.00       107
                    Chronic cholestasis       1.00      1.00      1.00       111
                            Common Cold       1.00      1.00      1.00       105
                                 Dengue       1.00      1.00      1.00       112
                              Diabetes        1.00      1.00      1.00       105
        Dimorphic hemmorhoids(piles)       1.00      1.00      1.00       109
                          Drug Reaction       1.00      1.00      1.00       106
                       Fungal infection       1.00      1.00      1.00       112
                                   GERD       1.00      1.00      1.00       108
                        Gastroenteritis       1.00      1.00      1.00       107
                           Heart attack       1.00      1.00      1.00       108
                            Hepatitis B       1.00      1.00      1.00       103
                            Hepatitis C       1.00      1.00      1.00       106
                            Hepatitis D       1.00      1.00      1.00       105
                            Hepatitis E       1.00      1.00      1.00       111
                          Hypertension        1.00      1.00      1.00       111
                        Hyperthyroidism       1.00      1.00      1.00       112
                           Hypoglycemia       1.00      1.00      1.00       112
                         Hypothyroidism       1.00      1.00      1.00       105
                               Impetigo       1.00      1.00      1.00       104
                               Jaundice       1.00      1.00      1.00       109
                                Malaria       1.00      1.00      1.00       110
                               Migraine       1.00      1.00      1.00       109
                        Osteoarthristis       1.00      1.00      1.00       107
           Paralysis (brain hemorrhage)       1.00      1.00      1.00       109
                    Peptic ulcer diseae       1.00      1.00      1.00       112
                              Pneumonia       1.00      1.00      1.00       106
                              Psoriasis       1.00      1.00      1.00       108
                           Tuberculosis       1.00      1.00      1.00       106
                                Typhoid       1.00      1.00      1.00       108
                Urinary tract infection       1.00      1.00      1.00       108
                         Varicose veins       1.00      1.00      1.00       108
                            hepatitis A       1.00      1.00      1.00       107

                               accuracy                           1.00      4428
                              macro avg       1.00      1.00      1.00      4428
                           weighted avg       1.00      1.00      1.00      4428
```

The model is a bit slow

GradientBoostingClassifier

In [145…

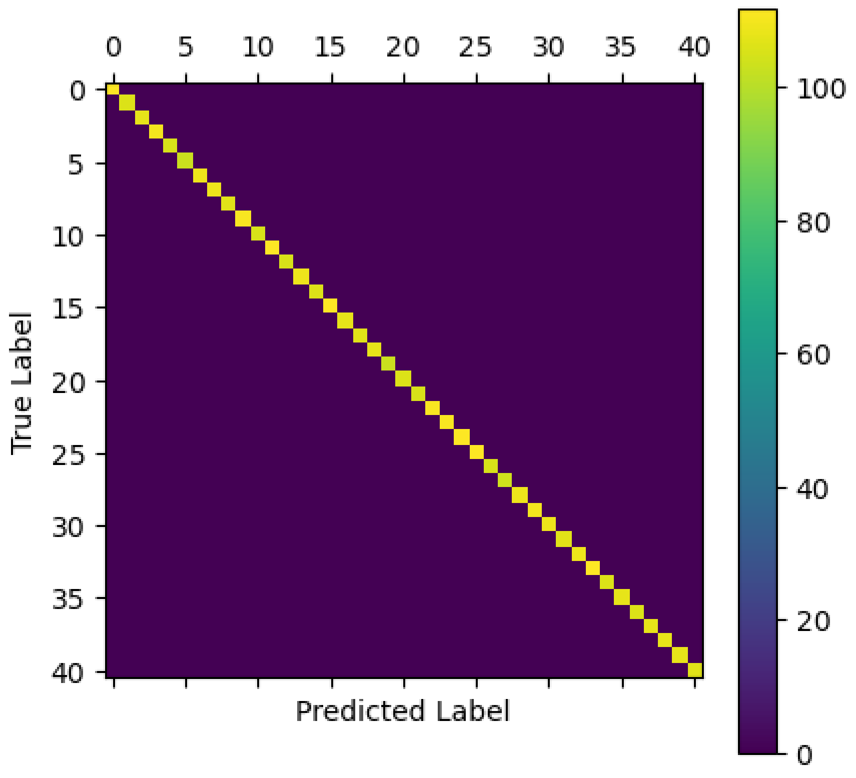
```
classifier_GB.fit(x_train, y_train)
y_predict = classifier_GB.predict(x_train)
```

```
# cross validation
scores = model_selection.cross_val_score(classifier_GB, x_train, y_train, cv = 10)

print(f'For Gradient Boosting Classifier, the accurracy is {round(scores.mean() * 1
    +/- {round(scores.std() * 1.96 / (10 ** 0.5), 2)}%')
```

```
For Gradient Boosting Classifier, the accurracy is 100.0    +/- 0.0%
```

In [146…

```
# plotting confusing matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

print(metrics.classification_report(y_train, y_predict))
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00       112
                                   AIDS       1.00      1.00      1.00       106
                                   Acne       1.00      1.00      1.00       108
                    Alcoholic hepatitis       1.00      1.00      1.00       110
                                Allergy       1.00      1.00      1.00       105
                              Arthritis       1.00      1.00      1.00       103
                       Bronchial Asthma       1.00      1.00      1.00       109
                   Cervical spondylosis       1.00      1.00      1.00       109
                            Chicken pox       1.00      1.00      1.00       107
                    Chronic cholestasis       1.00      1.00      1.00       111
                            Common Cold       1.00      1.00      1.00       105
                                 Dengue       1.00      1.00      1.00       112
                              Diabetes        1.00      1.00      1.00       105
           Dimorphic hemmorhoids(piles)       1.00      1.00      1.00       109
                          Drug Reaction       1.00      1.00      1.00       106
                       Fungal infection       1.00      1.00      1.00       112
                                   GERD       1.00      1.00      1.00       108
                       Gastroenteritis        1.00      1.00      1.00       107
                           Heart attack       1.00      1.00      1.00       108
                            Hepatitis B       1.00      1.00      1.00       103
                            Hepatitis C       1.00      1.00      1.00       106
                            Hepatitis D       1.00      1.00      1.00       105
                            Hepatitis E       1.00      1.00      1.00       111
                          Hypertension        1.00      1.00      1.00       111
                        Hyperthyroidism       1.00      1.00      1.00       112
                           Hypoglycemia       1.00      1.00      1.00       112
                         Hypothyroidism       1.00      1.00      1.00       105
                               Impetigo       1.00      1.00      1.00       104
                               Jaundice       1.00      1.00      1.00       109
                                Malaria       1.00      1.00      1.00       110
                               Migraine       1.00      1.00      1.00       109
                        Osteoarthristis       1.00      1.00      1.00       107
           Paralysis (brain hemorrhage)       1.00      1.00      1.00       109
                    Peptic ulcer diseae       1.00      1.00      1.00       112
                              Pneumonia       1.00      1.00      1.00       106
                              Psoriasis       1.00      1.00      1.00       108
                           Tuberculosis       1.00      1.00      1.00       106
                                Typhoid       1.00      1.00      1.00       108
                Urinary tract infection       1.00      1.00      1.00       108
                         Varicose veins       1.00      1.00      1.00       108
                            hepatitis A       1.00      1.00      1.00       107

                               accuracy                           1.00      4428
                              macro avg       1.00      1.00      1.00      4428
                           weighted avg       1.00      1.00      1.00      4428
```

This model is much slower...

GaussianNB

In [147...

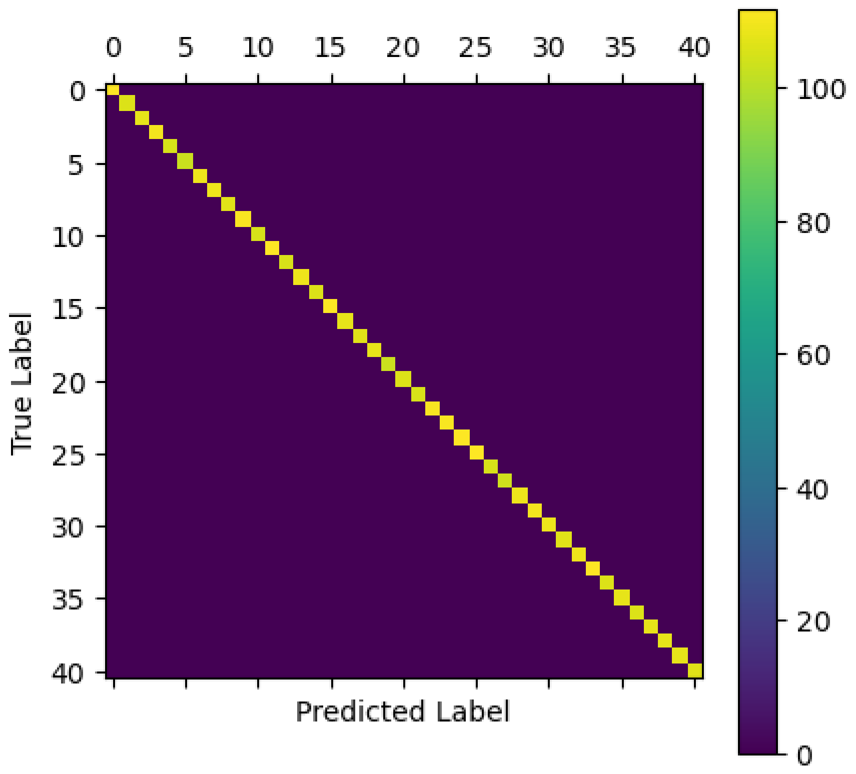
```
classifier_NB.fit(x_train, y_train)
y_predict = classifier_NB.predict(x_train)
```

```
# Cross Validation
scores = model_selection.cross_val_score(classifier_NB, x_train, y_train, cv = 10)
print(f'Fore Gaussian Naive Bayes Model, the accurracy is {round(scores.mean() * 10
```

```
Fore Gaussian Naive Bayes Model, the accurracy is 100.0 +/- 0.0
```

In [148…

```
# confusion matrix
cm = metrics.confusion_matrix(y_train, y_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
print(metrics.classification_report(y_train, y_predict))
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00       112
                                   AIDS       1.00      1.00      1.00       106
                                   Acne       1.00      1.00      1.00       108
                    Alcoholic hepatitis       1.00      1.00      1.00       110
                                Allergy       1.00      1.00      1.00       105
                              Arthritis       1.00      1.00      1.00       103
                       Bronchial Asthma       1.00      1.00      1.00       109
                   Cervical spondylosis       1.00      1.00      1.00       109
                            Chicken pox       1.00      1.00      1.00       107
                    Chronic cholestasis       1.00      1.00      1.00       111
                            Common Cold       1.00      1.00      1.00       105
                                 Dengue       1.00      1.00      1.00       112
                              Diabetes        1.00      1.00      1.00       105
        Dimorphic hemmorhoids(piles)          1.00      1.00      1.00       109
                          Drug Reaction       1.00      1.00      1.00       106
                       Fungal infection       1.00      1.00      1.00       112
                                   GERD       1.00      1.00      1.00       108
                        Gastroenteritis       1.00      1.00      1.00       107
                           Heart attack       1.00      1.00      1.00       108
                            Hepatitis B       1.00      1.00      1.00       103
                            Hepatitis C       1.00      1.00      1.00       106
                            Hepatitis D       1.00      1.00      1.00       105
                            Hepatitis E       1.00      1.00      1.00       111
                          Hypertension        1.00      1.00      1.00       111
                        Hyperthyroidism       1.00      1.00      1.00       112
                           Hypoglycemia       1.00      1.00      1.00       112
                         Hypothyroidism       1.00      1.00      1.00       105
                               Impetigo       1.00      1.00      1.00       104
                               Jaundice       1.00      1.00      1.00       109
                                Malaria       1.00      1.00      1.00       110
                               Migraine       1.00      1.00      1.00       109
                        Osteoarthristis       1.00      1.00      1.00       107
           Paralysis (brain hemorrhage)       1.00      1.00      1.00       109
                    Peptic ulcer diseae       1.00      1.00      1.00       112
                              Pneumonia       1.00      1.00      1.00       106
                              Psoriasis       1.00      1.00      1.00       108
                           Tuberculosis       1.00      1.00      1.00       106
                                Typhoid       1.00      1.00      1.00       108
                Urinary tract infection       1.00      1.00      1.00       108
                         Varicose veins       1.00      1.00      1.00       108
                            hepatitis A       1.00      1.00      1.00       107

                               accuracy                           1.00      4428
                              macro avg       1.00      1.00      1.00      4428
                           weighted avg       1.00      1.00      1.00      4428
```

All of the models above, including logistic regression, are overfitted. Let's see what they perform in test model.

4. Model Evaluation

Precision(PPV, positive predictive value): tp / (tp + fp); High Precision means low fp

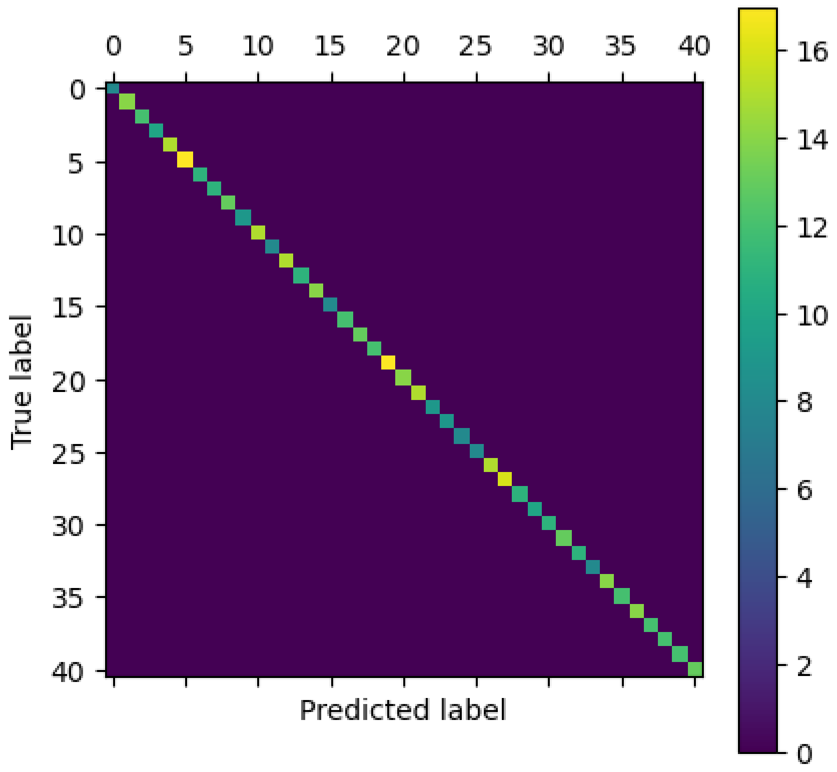
Recall(sensitivity, hit rate, true positive rate): tp / (tp + fn)

Accurracy: (tp + tn) / (tp + tn + fp + fn)

f1-Score: (2 * P * R) / (P + R)

1. Logistic Regression

In [149…
```
y_final_predict = classifier_logistic.predict(x_test)

cm = metrics.confusion_matrix(y_test, y_final_predict)
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, y_final_predict))
```



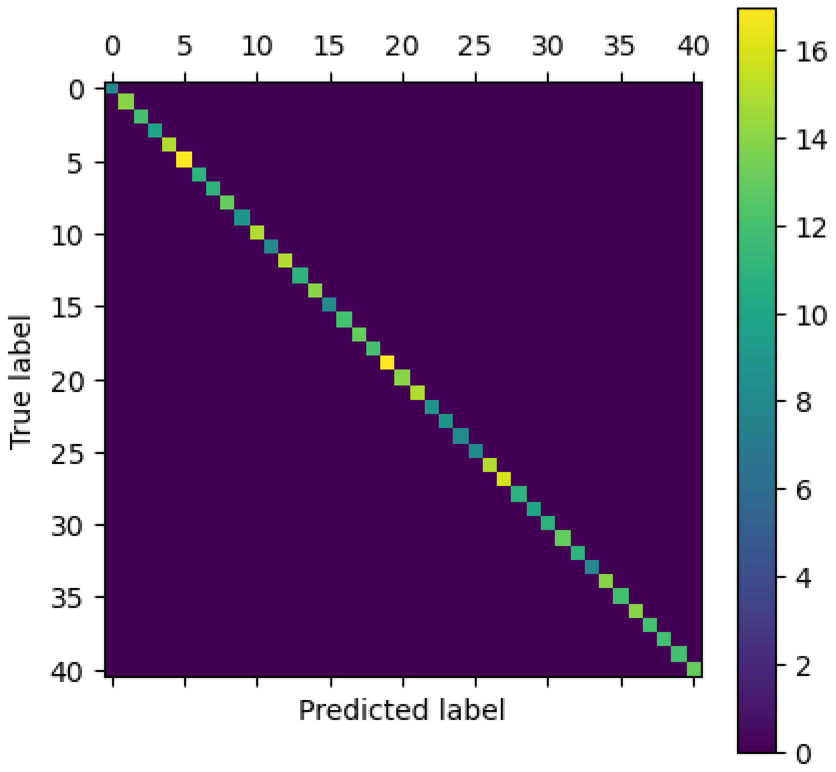
```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00         8
                                   AIDS       1.00      1.00      1.00        14
                                   Acne       1.00      1.00      1.00        12
                    Alcoholic hepatitis       1.00      1.00      1.00        10
                                Allergy       1.00      1.00      1.00        15
                              Arthritis       1.00      1.00      1.00        17
                       Bronchial Asthma       1.00      1.00      1.00        11
                   Cervical spondylosis       1.00      1.00      1.00        11
                            Chicken pox       1.00      1.00      1.00        13
                    Chronic cholestasis       1.00      1.00      1.00         9
                            Common Cold       1.00      1.00      1.00        15
                                 Dengue       1.00      1.00      1.00         8
                              Diabetes        1.00      1.00      1.00        15
         Dimorphic hemmorhoids(piles)         1.00      1.00      1.00        11
                          Drug Reaction       1.00      1.00      1.00        14
                       Fungal infection       1.00      1.00      1.00         8
                                   GERD       1.00      1.00      1.00        12
                        Gastroenteritis       1.00      1.00      1.00        13
                           Heart attack       1.00      1.00      1.00        12
                            Hepatitis B       1.00      1.00      1.00        17
                            Hepatitis C       1.00      1.00      1.00        14
                            Hepatitis D       1.00      1.00      1.00        15
                            Hepatitis E       1.00      1.00      1.00         9
                          Hypertension        1.00      1.00      1.00         9
                        Hyperthyroidism       1.00      1.00      1.00         8
                           Hypoglycemia       1.00      1.00      1.00         8
                         Hypothyroidism       1.00      1.00      1.00        15
                               Impetigo       1.00      1.00      1.00        16
                               Jaundice       1.00      1.00      1.00        11
                                Malaria       1.00      1.00      1.00        10
                               Migraine       1.00      1.00      1.00        11
                        Osteoarthristis       1.00      1.00      1.00        13
             Paralysis (brain hemorrhage)     1.00      1.00      1.00        11
                    Peptic ulcer diseae       1.00      1.00      1.00         8
                              Pneumonia       1.00      1.00      1.00        14
                              Psoriasis       1.00      1.00      1.00        12
                           Tuberculosis       1.00      1.00      1.00        14
                                Typhoid       1.00      1.00      1.00        12
                Urinary tract infection       1.00      1.00      1.00        12
                         Varicose veins       1.00      1.00      1.00        12
                            hepatitis A       1.00      1.00      1.00        13

                               accuracy                           1.00       492
                              macro avg       1.00      1.00      1.00       492
                           weighted avg       1.00      1.00      1.00       492
```

If we only use patient symptom data for diagnosis, a logistic regression might be enough...
However, it might be a bit unrealistic because the disease diagnosis task is a relative complexed one
This dataset seems to be a bit ideal.

2. RandomForestClassifier

In [150…

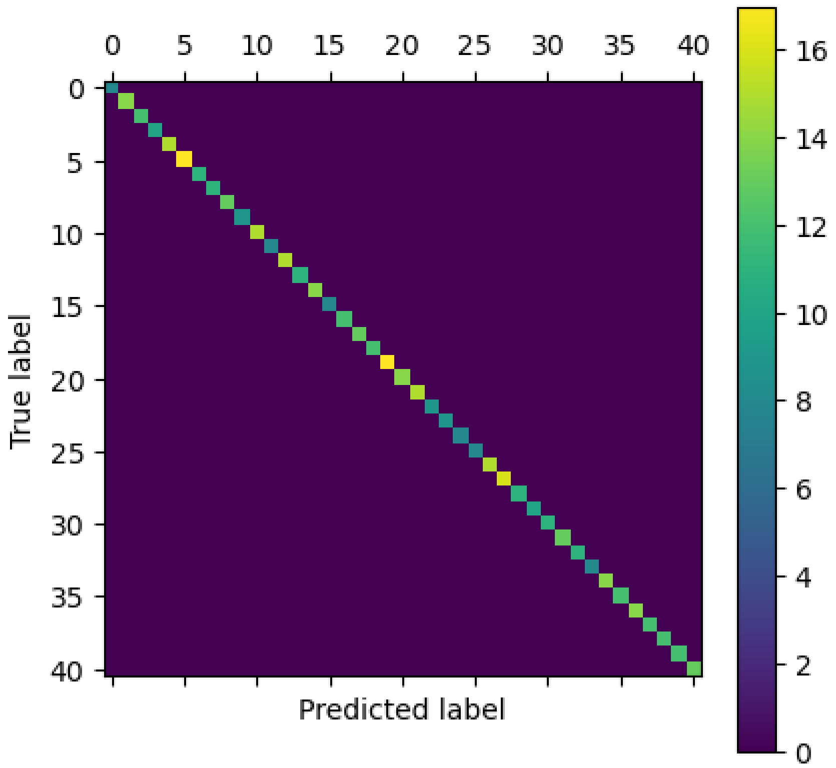
```
# Confusion Matrix
cm = metrics.confusion_matrix(y_test, classifier_RF.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, classifier_RF.predict(x_test)))
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00         8
                                   AIDS       1.00      1.00      1.00        14
                                   Acne       1.00      1.00      1.00        12
                    Alcoholic hepatitis       1.00      1.00      1.00        10
                                Allergy       1.00      1.00      1.00        15
                              Arthritis       1.00      1.00      1.00        17
                       Bronchial Asthma       1.00      1.00      1.00        11
                   Cervical spondylosis       1.00      1.00      1.00        11
                            Chicken pox       1.00      1.00      1.00        13
                    Chronic cholestasis       1.00      1.00      1.00         9
                            Common Cold       1.00      1.00      1.00        15
                                 Dengue       1.00      1.00      1.00         8
                              Diabetes        1.00      1.00      1.00        15
        Dimorphic hemmorhoids(piles)       1.00      1.00      1.00        11
                          Drug Reaction       1.00      1.00      1.00        14
                       Fungal infection       1.00      1.00      1.00         8
                                   GERD       1.00      1.00      1.00        12
                        Gastroenteritis       1.00      1.00      1.00        13
                           Heart attack       1.00      1.00      1.00        12
                            Hepatitis B       1.00      1.00      1.00        17
                            Hepatitis C       1.00      1.00      1.00        14
                            Hepatitis D       1.00      1.00      1.00        15
                            Hepatitis E       1.00      1.00      1.00         9
                          Hypertension        1.00      1.00      1.00         9
                        Hyperthyroidism       1.00      1.00      1.00         8
                           Hypoglycemia       1.00      1.00      1.00         8
                         Hypothyroidism       1.00      1.00      1.00        15
                               Impetigo       1.00      1.00      1.00        16
                               Jaundice       1.00      1.00      1.00        11
                                Malaria       1.00      1.00      1.00        10
                               Migraine       1.00      1.00      1.00        11
                        Osteoarthristis       1.00      1.00      1.00        13
         Paralysis (brain hemorrhage)       1.00      1.00      1.00        11
                    Peptic ulcer diseae       1.00      1.00      1.00         8
                              Pneumonia       1.00      1.00      1.00        14
                              Psoriasis       1.00      1.00      1.00        12
                           Tuberculosis       1.00      1.00      1.00        14
                                Typhoid       1.00      1.00      1.00        12
                Urinary tract infection       1.00      1.00      1.00        12
                         Varicose veins       1.00      1.00      1.00        12
                            hepatitis A       1.00      1.00      1.00        13

                               accuracy                           1.00       492
                              macro avg       1.00      1.00      1.00       492
                           weighted avg       1.00      1.00      1.00       492
```

3. KNeighborsClassifier

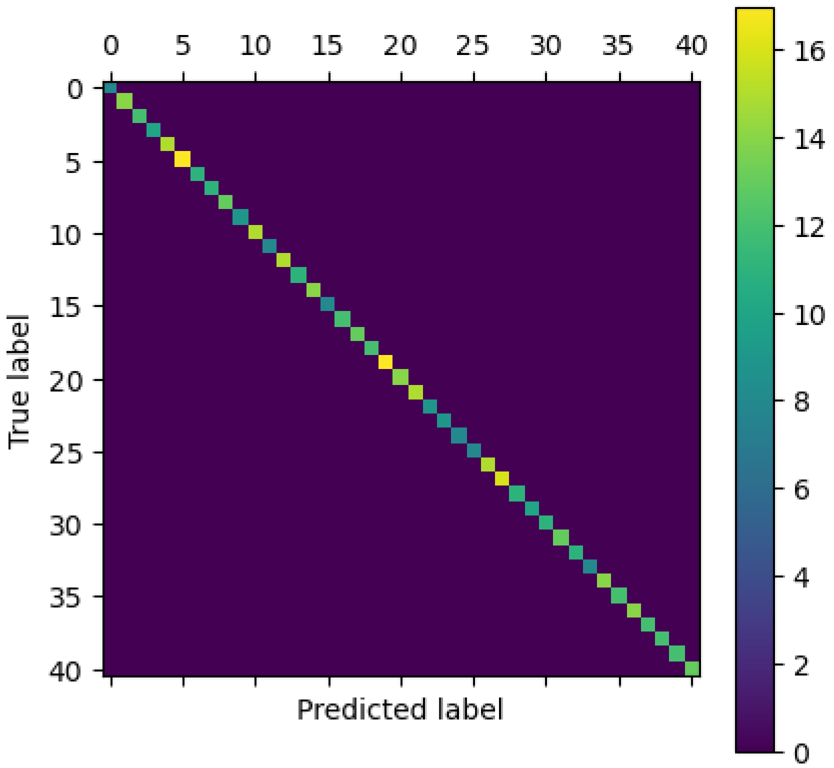
In [151…
```
# Confusion Matrix
cm = metrics.confusion_matrix(y_test, classifier_KNN.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, classifier_KNN.predict(x_test)))
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00         8
                                   AIDS       1.00      1.00      1.00        14
                                   Acne       1.00      1.00      1.00        12
                    Alcoholic hepatitis       1.00      1.00      1.00        10
                                Allergy       1.00      1.00      1.00        15
                              Arthritis       1.00      1.00      1.00        17
                       Bronchial Asthma       1.00      1.00      1.00        11
                   Cervical spondylosis       1.00      1.00      1.00        11
                            Chicken pox       1.00      1.00      1.00        13
                    Chronic cholestasis       1.00      1.00      1.00         9
                            Common Cold       1.00      1.00      1.00        15
                                 Dengue       1.00      1.00      1.00         8
                              Diabetes        1.00      1.00      1.00        15
           Dimorphic hemmorhoids(piles)       1.00      1.00      1.00        11
                          Drug Reaction       1.00      1.00      1.00        14
                       Fungal infection       1.00      1.00      1.00         8
                                   GERD       1.00      1.00      1.00        12
                        Gastroenteritis       1.00      1.00      1.00        13
                           Heart attack       1.00      1.00      1.00        12
                            Hepatitis B       1.00      1.00      1.00        17
                            Hepatitis C       1.00      1.00      1.00        14
                            Hepatitis D       1.00      1.00      1.00        15
                            Hepatitis E       1.00      1.00      1.00         9
                          Hypertension        1.00      1.00      1.00         9
                        Hyperthyroidism       1.00      1.00      1.00         8
                           Hypoglycemia       1.00      1.00      1.00         8
                         Hypothyroidism       1.00      1.00      1.00        15
                               Impetigo       1.00      1.00      1.00        16
                               Jaundice       1.00      1.00      1.00        11
                                Malaria       1.00      1.00      1.00        10
                               Migraine       1.00      1.00      1.00        11
                        Osteoarthristis       1.00      1.00      1.00        13
             Paralysis (brain hemorrhage)       1.00      1.00      1.00        11
                    Peptic ulcer diseae       1.00      1.00      1.00         8
                              Pneumonia       1.00      1.00      1.00        14
                              Psoriasis       1.00      1.00      1.00        12
                           Tuberculosis       1.00      1.00      1.00        14
                                Typhoid       1.00      1.00      1.00        12
                Urinary tract infection       1.00      1.00      1.00        12
                         Varicose veins       1.00      1.00      1.00        12
                            hepatitis A       1.00      1.00      1.00        13

                               accuracy                           1.00       492
                              macro avg       1.00      1.00      1.00       492
                           weighted avg       1.00      1.00      1.00       492
```

4. SVC

In [152…
```
# confusion matrix
cm = metrics.confusion_matrix(y_test, classifier_SVC.predict(x_test))
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True label')
plt.xlabel('Predicted label')
plt.show()

print(metrics.classification_report(y_test, classifier_SVC.predict(x_test)))
```



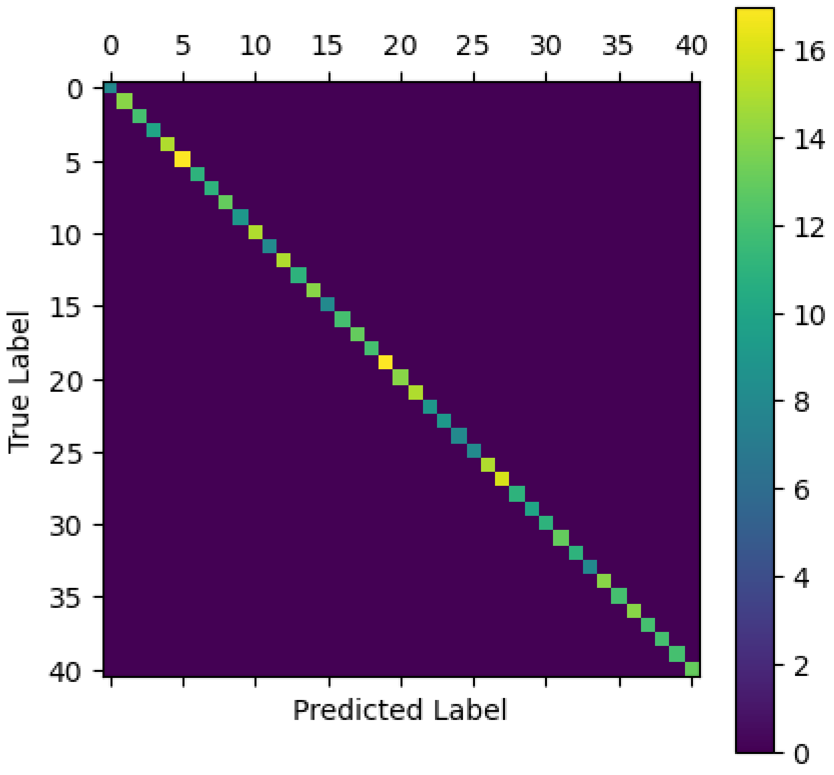
```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00         8
                                   AIDS       1.00      1.00      1.00        14
                                   Acne       1.00      1.00      1.00        12
                    Alcoholic hepatitis       1.00      1.00      1.00        10
                                Allergy       1.00      1.00      1.00        15
                              Arthritis       1.00      1.00      1.00        17
                       Bronchial Asthma       1.00      1.00      1.00        11
                   Cervical spondylosis       1.00      1.00      1.00        11
                            Chicken pox       1.00      1.00      1.00        13
                    Chronic cholestasis       1.00      1.00      1.00         9
                            Common Cold       1.00      1.00      1.00        15
                                 Dengue       1.00      1.00      1.00         8
                              Diabetes        1.00      1.00      1.00        15
        Dimorphic hemmorhoids(piles)       1.00      1.00      1.00        11
                          Drug Reaction       1.00      1.00      1.00        14
                       Fungal infection       1.00      1.00      1.00         8
                                   GERD       1.00      1.00      1.00        12
                        Gastroenteritis       1.00      1.00      1.00        13
                           Heart attack       1.00      1.00      1.00        12
                            Hepatitis B       1.00      1.00      1.00        17
                            Hepatitis C       1.00      1.00      1.00        14
                            Hepatitis D       1.00      1.00      1.00        15
                            Hepatitis E       1.00      1.00      1.00         9
                          Hypertension        1.00      1.00      1.00         9
                        Hyperthyroidism       1.00      1.00      1.00         8
                           Hypoglycemia       1.00      1.00      1.00         8
                         Hypothyroidism       1.00      1.00      1.00        15
                               Impetigo       1.00      1.00      1.00        16
                               Jaundice       1.00      1.00      1.00        11
                                Malaria       1.00      1.00      1.00        10
                               Migraine       1.00      1.00      1.00        11
                        Osteoarthristis       1.00      1.00      1.00        13
           Paralysis (brain hemorrhage)       1.00      1.00      1.00        11
                    Peptic ulcer diseae       1.00      1.00      1.00         8
                              Pneumonia       1.00      1.00      1.00        14
                              Psoriasis       1.00      1.00      1.00        12
                           Tuberculosis       1.00      1.00      1.00        14
                                Typhoid       1.00      1.00      1.00        12
                Urinary tract infection       1.00      1.00      1.00        12
                         Varicose veins       1.00      1.00      1.00        12
                            hepatitis A       1.00      1.00      1.00        13

                               accuracy                           1.00       492
                              macro avg       1.00      1.00      1.00       492
                           weighted avg       1.00      1.00      1.00       492
```

The model is a bit slow

5. GradientBoostingClassifier

In [153…
```
# plotting confusing matrix
cm = metrics.confusion_matrix(y_test, classifier_GB.predict(x_test))
```

```
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()

print(metrics.classification_report(y_test, classifier_GB.predict(x_test)))
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00         8
                                   AIDS       1.00      1.00      1.00        14
                                   Acne       1.00      1.00      1.00        12
                    Alcoholic hepatitis       1.00      1.00      1.00        10
                                Allergy       1.00      1.00      1.00        15
                              Arthritis       1.00      1.00      1.00        17
                       Bronchial Asthma       1.00      1.00      1.00        11
                   Cervical spondylosis       1.00      1.00      1.00        11
                            Chicken pox       1.00      1.00      1.00        13
                    Chronic cholestasis       1.00      1.00      1.00         9
                            Common Cold       1.00      1.00      1.00        15
                                 Dengue       1.00      1.00      1.00         8
                              Diabetes        1.00      1.00      1.00        15
        Dimorphic hemmorhoids(piles)       1.00      1.00      1.00        11
                          Drug Reaction       1.00      1.00      1.00        14
                       Fungal infection       1.00      1.00      1.00         8
                                   GERD       1.00      1.00      1.00        12
                        Gastroenteritis       1.00      1.00      1.00        13
                           Heart attack       1.00      1.00      1.00        12
                            Hepatitis B       1.00      1.00      1.00        17
                            Hepatitis C       1.00      1.00      1.00        14
                            Hepatitis D       1.00      1.00      1.00        15
                            Hepatitis E       1.00      1.00      1.00         9
                          Hypertension        1.00      1.00      1.00         9
                        Hyperthyroidism       1.00      1.00      1.00         8
                           Hypoglycemia       1.00      1.00      1.00         8
                         Hypothyroidism       1.00      1.00      1.00        15
                               Impetigo       1.00      1.00      1.00        16
                               Jaundice       1.00      1.00      1.00        11
                                Malaria       1.00      1.00      1.00        10
                               Migraine       1.00      1.00      1.00        11
                        Osteoarthristis       1.00      1.00      1.00        13
             Paralysis (brain hemorrhage)       1.00      1.00      1.00        11
                    Peptic ulcer diseae       1.00      1.00      1.00         8
                              Pneumonia       1.00      1.00      1.00        14
                              Psoriasis       1.00      1.00      1.00        12
                           Tuberculosis       1.00      1.00      1.00        14
                                Typhoid       1.00      1.00      1.00        12
                Urinary tract infection       1.00      1.00      1.00        12
                         Varicose veins       1.00      1.00      1.00        12
                            hepatitis A       1.00      1.00      1.00        13

                               accuracy                           1.00       492
                              macro avg       1.00      1.00      1.00       492
                           weighted avg       1.00      1.00      1.00       492
```

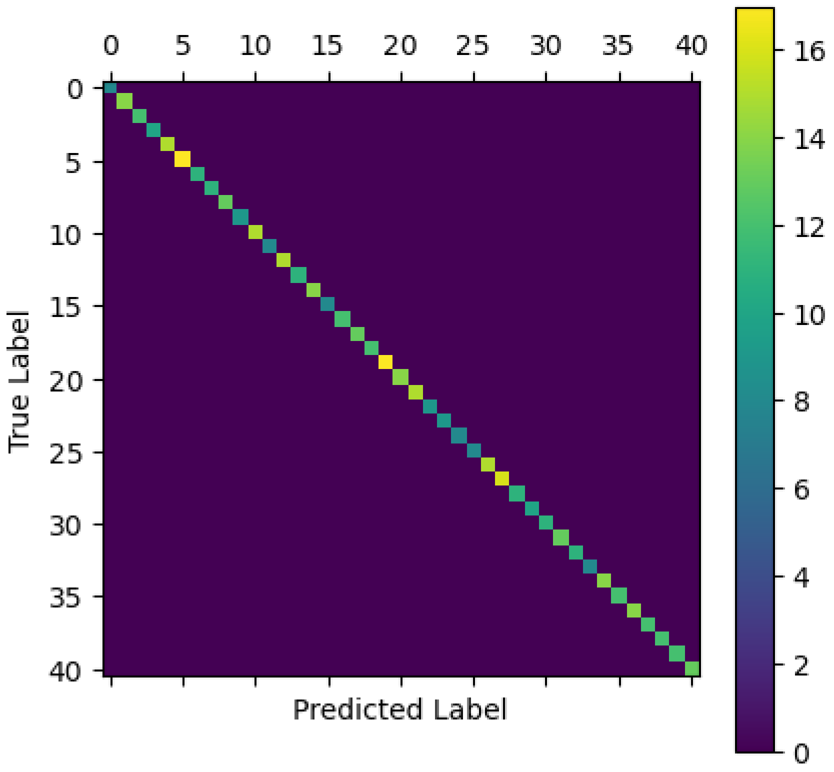
This model is much slower...

GaussianNB

In [154...

```
# confusion matrix
cm = metrics.confusion_matrix(y_test, classifier_NB.predict(x_test))
```

```
plt.matshow(cm)
plt.colorbar()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
print(metrics.classification_report(y_test, classifier_NB.predict(x_test)))
```



```
                                         precision    recall  f1-score   support

(vertigo) Paroymsal  Positional Vertigo       1.00      1.00      1.00         8
                                   AIDS       1.00      1.00      1.00        14
                                   Acne       1.00      1.00      1.00        12
                    Alcoholic hepatitis       1.00      1.00      1.00        10
                                Allergy       1.00      1.00      1.00        15
                              Arthritis       1.00      1.00      1.00        17
                       Bronchial Asthma       1.00      1.00      1.00        11
                   Cervical spondylosis       1.00      1.00      1.00        11
                            Chicken pox       1.00      1.00      1.00        13
                    Chronic cholestasis       1.00      1.00      1.00         9
                            Common Cold       1.00      1.00      1.00        15
                                 Dengue       1.00      1.00      1.00         8
                              Diabetes        1.00      1.00      1.00        15
        Dimorphic hemmorhoids(piles)       1.00      1.00      1.00        11
                          Drug Reaction       1.00      1.00      1.00        14
                       Fungal infection       1.00      1.00      1.00         8
                                   GERD       1.00      1.00      1.00        12
                        Gastroenteritis       1.00      1.00      1.00        13
                           Heart attack       1.00      1.00      1.00        12
                            Hepatitis B       1.00      1.00      1.00        17
                            Hepatitis C       1.00      1.00      1.00        14
                            Hepatitis D       1.00      1.00      1.00        15
                            Hepatitis E       1.00      1.00      1.00         9
                          Hypertension        1.00      1.00      1.00         9
                        Hyperthyroidism       1.00      1.00      1.00         8
                           Hypoglycemia       1.00      1.00      1.00         8
                         Hypothyroidism       1.00      1.00      1.00        15
                               Impetigo       1.00      1.00      1.00        16
                               Jaundice       1.00      1.00      1.00        11
                                Malaria       1.00      1.00      1.00        10
                               Migraine       1.00      1.00      1.00        11
                        Osteoarthristis       1.00      1.00      1.00        13
           Paralysis (brain hemorrhage)       1.00      1.00      1.00        11
                    Peptic ulcer diseae       1.00      1.00      1.00         8
                              Pneumonia       1.00      1.00      1.00        14
                              Psoriasis       1.00      1.00      1.00        12
                           Tuberculosis       1.00      1.00      1.00        14
                                Typhoid       1.00      1.00      1.00        12
                Urinary tract infection       1.00      1.00      1.00        12
                         Varicose veins       1.00      1.00      1.00        12
                            hepatitis A       1.00      1.00      1.00        13

                               accuracy                           1.00       492
                              macro avg       1.00      1.00      1.00       492
                           weighted avg       1.00      1.00      1.00       492
```

All of the models above, including logistic regression, are overfitted, even in testing data.

Therefore, if we have to figure out which one is the best, maybe the only answer would be the **logistic regression** model

Feature Importance

In [155…

```
importances = classifier_RF.feature_importances_

indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature importance ranking by RF:")
for ind in range(x.shape[1]):
  print ("{0} : {1}".format(x.columns[indices[ind]],round(importances[indices[ind]]
Feature importance ranking by RF:
 muscle_pain : 0.0195
 chest_pain : 0.0164
itching : 0.0151
 yellowing_of_eyes : 0.0151
 altered_sensorium : 0.0149
 diarrhoea : 0.0144
 dark_urine : 0.0144
 lack_of_concentration : 0.014
 family_history : 0.0135
 weight_loss : 0.0131
 mild_fever : 0.0129
 vomiting : 0.0128
 mucoid_sputum : 0.0126
 unsteadiness : 0.0125
 joint_pain : 0.0123
 red_spots_over_body : 0.012
 nausea : 0.012
 fatigue : 0.0119
 chills : 0.0117
 loss_of_balance : 0.0117
 internal_itching : 0.0117
 loss_of_appetite : 0.0114
 abdominal_pain : 0.0114
 high_fever : 0.0114
 bladder_discomfort : 0.0114
 muscle_weakness : 0.0113
 headache : 0.0112
 sweating : 0.0111
 stomach_pain : 0.0109
 coma : 0.0108
 irritability : 0.0107
 dischromic _patches : 0.0105
 pain_behind_the_eyes : 0.0105
 rusty_sputum : 0.0104
 spotting_ urination : 0.0103
 breathlessness : 0.0103
 back_pain : 0.0102
 nodal_skin_eruptions : 0.0096
 patches_in_throat : 0.0092
 blackheads : 0.0091
 fluid_overload : 0.0091
 stomach_bleeding : 0.009
 increased_appetite : 0.0088
 fast_heart_rate : 0.0088
 continuous_feel_of_urine : 0.0086
 silver_like_dusting : 0.0086
 receiving_unsterile_injections : 0.0085
 yellowish_skin : 0.0085
 palpitations : 0.0084
 malaise : 0.0082
 pus_filled_pimples : 0.0081
 passage_of_gases : 0.008
 blood_in_sputum : 0.0079
 hip_joint_pain : 0.0079
 blister : 0.0078
```

```
yellow_crust_ooze : 0.0077
sunken_eyes : 0.0077
swelling_joints : 0.0076
neck_pain : 0.0076
continuous_sneezing : 0.0074
swelling_of_stomach : 0.0073
cough : 0.0073
weakness_of_one_body_side : 0.0073
swelled_lymph_nodes : 0.0072
dehydration : 0.0072
phlegm : 0.0071
belly_pain : 0.0071
polyuria : 0.0069
receiving_blood_transfusion : 0.0069
movement_stiffness : 0.0068
prominent_veins_on_calf : 0.0068
slurred_speech : 0.0067
pain_in_anal_region : 0.0067
extra_marital_contacts : 0.0067
red_sore_around_nose : 0.0067
toxic_look_(typhos) : 0.0065
burning_micturition : 0.0065
abnormal_menstruation : 0.0065
inflammatory_nails : 0.0064
ulcers_on_tongue : 0.0063
shivering : 0.0062
spinning_movements : 0.0061
depression : 0.0061
acidity : 0.0059
pain_during_bowel_movements : 0.0059
excessive_hunger : 0.0059
constipation : 0.0057
scurring : 0.0056
watering_from_eyes : 0.0056
cramps : 0.0055
dizziness : 0.0055
brittle_nails : 0.0054
indigestion : 0.0054
skin_rash : 0.0053
stiff_neck : 0.0051
acute_liver_failure : 0.005
knee_pain : 0.005
distention_of_abdomen : 0.0047
painful_walking : 0.0047
irritation_in_anus : 0.0047
bloody_stool : 0.0046
muscle_wasting : 0.0046
loss_of_smell : 0.0045
restlessness : 0.0044
throat_irritation : 0.0043
enlarged_thyroid : 0.0043
visual_disturbances : 0.0043
skin_peeling : 0.0043
blurred_and_distorted_vision : 0.0042
small_dents_in_nails : 0.0041
lethargy : 0.004
```

```
swollen_extremeties : 0.004
weakness_in_limbs : 0.0038
history_of_alcohol_consumption : 0.0038
congestion : 0.0038
obesity : 0.0037
runny_nose : 0.0034
swollen_legs : 0.0034
bruising : 0.0034
mood_swings : 0.0031
anxiety : 0.0031
yellow_urine : 0.0027
redness_of_eyes : 0.0025
weight_gain : 0.0024
drying_and_tingling_lips : 0.0024
irregular_sugar_level : 0.0024
swollen_blood_vessels : 0.0021
sinus_pressure : 0.002
foul_smell_of urine : 0.0017
cold_hands_and_feets : 0.0014
puffy_face_and_eyes : 0.0009
```

5. Insigits & Conclusion

1. It seems that logistic regression is enough to diagnose some common disease.
However, the usability of this model is still needed to be furtherly verified due to the possible overly-ideal.
2. muscle pain, chest pain, itching, yellowing of eyes, and altered sensorium are 5 symptoms with high specificity.