

Disease Prediction Using Machine Learning

Raneen Alshehri 2005560 Ghaid Althobaity 2005564

Noor O. Alamoudi 2005841

Taif A. Basheikh 2005890

Raghad Alqithmi 2005999

Applied machine learning project

Dr. Enas Abo Fateh

2023





CONTENT

- 1-INTRODUCTION
- 2-PROBLEM DEFINITION AND OBJECTIVES
- 3-APPROACH
 - 3.1 DATA SET
 - 3.2 DATA COLLECTION
 - 3.3 MACHINE LEARNING MODEL
 - 3.3.1 RANDOM FOREST CLASSIDIER
- 4- ANALYSIS AND RESULTS
 - 4.1 QUESTION / HYPOTHESIS
 - 4.2 CODE AND ANALYSIS
 - 4.3 IMPORTING THE DATA
 - 4.4 PREPROCESSING
 - 4.5 SPLITTING THE DATA
 - 4.6 TRAINING THE MODEL
 - 4.7 PERFORMANCE
- 5- CONCLUSION
- 6- REFERENCE
- 7- APPENDIX



Introduction

People face various diseases due environmental condition and their living habits. So the prediction of disease at earlier stage becomes important task. But the accurate prediction on the basis of symptoms becomes too difficult for doctor. The correct prediction of disease is the most challenging task, and medical science has large amount of data growth per year. Due to increase amount of data growth in medical and healthcare field the accurate analysis on medical data has been benefits from early patient care. So, we proposed Disease Prediction Using Machine Learning



PROPLEM DEFINITION & OBJECTIVES

The purpose of constructing this project called "Disease Prediction Using Machine Learning" is to predict the accurate disease of the patient using all their general information's and also the symptoms. If this Prediction is completed at the first stages of the disease with the assistance of this project and everyone other necessary, measure disease is cured and generally this prediction system can even be very useful in health industry. The final purpose of this Disease prediction is to supply prediction for the assorted and customarily occurring diseases that when unchecked and sometimes ignored can turns into fatal disease and cause lot of problem to the patient and moreover as their members of the family. So, with the assistance of algorithms, techniques and methodologies we've done this project which is able to help the peoples who are within the need.

APPROCH:

DATA SET

The dataset we will use in our project is Disease Prediction consists of 2 CSV files. One of them is for training and the other is for testing your model. Each CSV file has 133 columns. 132 of these columns are symptoms that a person experiences and the last column is the prognosis. And making the task of physicians easy is the main purpose of this dataset. Determined by the type of disease using the Random Forest model.

DATA COLLECTION

We download the Disease Prediction dataset from Kaggle, and this is the website https://www.kaggle.com/datasets/kaushil26 8/disease-prediction-using-machine-learning Because our project is Disease Prediction Using a Machine Learning scenario, we need to choose a dataset containing various diseases. The dataset selected is the best between different data on the same subject because it contains many types of diseases and symptoms.

MACHINE LEARNING MODEL

We have tried multiple prediction models but using the Random Forest classifier model has shown the best results:

Random Forest classifier

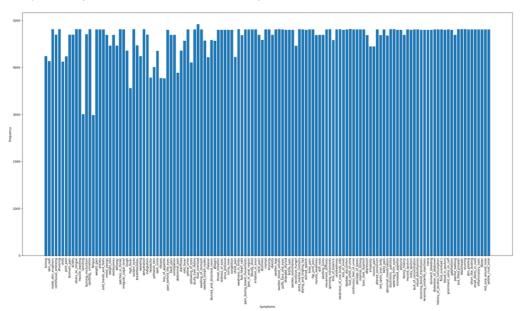
Random Forest classifier

The random forest classifier is a supervised learning algorithm that you can use for regression and classification problems. It is among the most popular machine learning algorithms due to its high flexibility and ease of implementation. So, The Random Forest is an ensemble learning method that can give more accurate predictions than most other machine learning algorithms. It is commonly used in decision tree learning. A forest is created using decision trees, each decision tree is a strong classifier on its own. These decision trees are used to create a forest of strong classifiers. This forest of strong classifiers gives a better prediction than decision trees or other machine learning algorithms.



Question/hypothesis

This picture shows the frequency of the symptom, we see that many of the symptoms occurred at about the same times, and the conclusion from this analysis inspired us to write these questions.



Predict whether the symptoms indicate a specific disease or not?

Is the increase in the proportion of symptoms a good indicator for the diagnosis of the disease or not?



Code and Analysis

We start with initial libraries such as:

- " Panda's library "is used in data analysis and data visualization in Python. It allows you to import data quickly from various sources, take it back to your machine to analyze it, and create compelling graphics.
- "Sklearn and Model_selection" Sklearn It is a Python library that offers various features for data processing that can be used for classification, clustering, and model selection. Model_selection is a method for setting a blueprint to analyze data and then using it to measure new data. Selecting a proper model allows you to generate accurate results when making a prediction. "train_test_split" is a function in Sklearn model selection for splitting data arrays into two subsets: for training data and for testing data.
- " Sklearn metrics " are import metrics in SciKit Learn API to evaluate your machine learning algorithms.
- And For training the "random forest classifier "we have used sklearn RandomForestClassifier to make a classifier model. We are keeping most of its parameters as default and then pass our training data to fit.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
```

Importing the Data

Our data is divided into 2 files, Training and Testing. We used the read_csv() method provided by pandas to import our CSV files and assign it to our variables - train and test.

Import Data

```
train = pd.read_csv('Dataset/Training.csv')
test = pd.read_csv('Dataset/Testing.csv')
```

Preprocessing

Before splitting our data, we have to pre-process it to make sure the data is ready to be trained. Firstly, we check for missing (Nan) values. Using the isnull() function. It is visible that all features have 'False' as a result, meaning no missing values.

Preprocess

```
# check for null values
train.isnull().any()
```

itching	False	yellow_urine	False
skin_rash	False	yellowing_of_eyes	False
nodal_skin_eruptions	False	acute_liver_failure	False
continuous_sneezing	False	fluid overload	False
shivering	False	swelling_of_stomach	False
chills	False	swelled_lymph_nodes	False
joint_pain	False	malaise	False
stomach pain	False	blurred_and_distorted_vision	False
acidity	False	phlegm	False
ulcers_on_tongue	False	throat_irritation	False
muscle_wasting	False	redness_of_eyes	False
vomiting	False	sinus pressure	False
burning micturition	False	runny_nose	False
spotting_urination	False	congestion	False
fatigue	False	chest_pain	False
weight_gain	False	weakness_in_limbs	False
anxiety	False	fast heart rate	False
cold_hands_and_feets	False	pain_during_bowel_movements	False
mood_swings	False	pain_in_anal_region	False
weight_loss	False	bloody_stool	False
restlessness	False	irritation_in_anus	False
lethargy	False	neck pain	False
patches_in_throat	False	dizziness	False
irregular_sugar_level	False	cramps	False
cough	False	bruising	False
high fever	False	obesity	False
sunken_eyes	False	swollen_legs	False
breathlessness	False	swollen_legs swollen_blood_vessels	False
sweating	False	puffy_face_and_eyes	False
dehydration	False	enlarged_thyroid	False
indigestion	False	brittle_nails	False
headache	False	swollen_extremeties	False
yellowish_skin	False	excessive_hunger	False
dark_urine	False	extra_marital_contacts	False
nausea	False	drying and tingling lips	False
nausea	raise	ar.Atu8_aua_ctu8ttu8_ttb2	raise

```
False loss_of_appetite
                                                                           False
spinning_movements
                                         pain_behind_the_eyes
                                                                           False
loss_of_balance
                                  False
                                                                           False
unsteadiness
                                  False
                                         back pain
weakness_of_one_body_side
                                         constipation
                                                                           False
                                  False
loss of smell
                                                                           False
                                  False
                                         abdominal pain
bladder_discomfort
                                  False
                                                                           False
                                         diarrhoea
foul_smell_of urine
                                  False
                                         mild fever
                                                                           False
continuous_feel_of_urine
                                  False
                                         slurred_speech
                                                                           False
passage of gases
                                  False
                                                                           False
                                         knee pain
internal itching
                                  False
                                         hip_joint_pain
                                                                           False
toxic look (typhos)
                                  False
                                         muscle weakness
                                                                           False
                                  False
depression
                                         stiff_neck
                                                                           False
irritability
                                  False
                                         swelling joints
                                                                           False
muscle_pain
                                 False
                                         movement_stiffness
                                                                           False
altered sensorium
                                  False
                                         silver_like_dusting
                                                                           False
red_spots_over_body
                                  False
                                         small_dents_in_nails
                                                                           False
belly pain
                                  False
                                         inflammatory_nails
                                                                           False
                                 False
abnormal_menstruation
                                         blister
                                                                           False
dischromic _patches
                                 False
                                         red_sore_around_nose
                                                                           False
                                 False
watering_from_eyes
                                 False yellow_crust_ooze
                                                                           False
increased_appetite
                                 False prognosis
                                                                           False
polyuria
                                  False
family history
mucoid_sputum
                                  False
                                  False
rusty_sputum
lack of concentration
                                  False
visual_disturbances
                                  False
receiving blood transfusion
                                  False
receiving_unsterile_injections
                                  False
                                  False
                                  False
stomach_bleeding
distention_of_abdomen
                                  False
history_of_alcohol_consumption
                                  False
fluid overload.1
                                  False
blood in sputum
                                  False
prominent_veins_on_calf
                                  False
palpitations
                                  False
painful_walking
                                  False
pus_filled_pimples
                                  False
blackheads
                                  False
                                  False
scurring
skin_peeling
                                  False
```

We've also displayed how much the diseases were mentioned in the set to make sure the data is unbiased. Using the value_counts() function to count the records of each disease, we observe that each disease has exactly 120 records, meaning the data is balanced and unbiased.

```
# check if balanced
train['prognosis'].value_counts()
```

Fungal infection	120	Allergy	120
Hepatitis C	120	hepatitis A	120
Hepatitis E	120	GERD	120
Alcoholic hepatitis	120	Chronic cholestasis	120
Tuberculosis	120	Drug Reaction	120
Common Cold	120	Peptic ulcer diseae	120
Pneumonia	120	AIDS	120
Dimorphic hemmorhoids(piles)	120	Diabetes	120
Heart attack	120	Gastroenteritis	120
Varicose veins	120	Bronchial Asthma	120
Hypothyroidism	120	Hypertension	120
Hyperthyroidism	120	Migraine	120
Hypoglycemia	120	•	
Osteoarthristis	120	Cervical spondylosis	120
Arthritis	120	Paralysis (brain hemorrhage)	120
(vertigo) Paroymsal Positional Vertigo	120	Jaundice	120
Acne	120	Malaria	120
Urinary tract infection	120	Chicken pox	120
Psoriasis	120	Dengue	120
Hepatitis D	120	Typhoid	120
Hepatitis B	120	Impetigo	120

Splitting the data

Now comes the splitting! We divide the training data to diseases and symptoms, A and B alternately. Then we split the data into 80% training and 20% testing datasets for the purpose of training and testing the model to help determine the accuracy of the machine learning algorithm. C will contain the symptoms from the testing csv file, that we will use to compare the actual and predicted value.

Split data

```
A = train[["prognosis"]] # diseases
B = train.drop(["prognosis"],axis=1) # symptoms
C = test.drop(["prognosis"],axis=1) # symptoms - testing
x_train, x_test, y_train, y_test = train_test_split(B,A,test_size=0.2)
```

Training the model

We set parameters:

- n_estimators: The number of trees in the forest = 100
- criterion: The function to measure the quality of a split = entropy (Used for information gain).
- n_jobs: The number of jobs to run in parallel = 5
- random_statet: Controls sampling and the randomness of bootstrapping = 42

Fitting the model, using fit(), to the training data is essentially the training part of the modelling process. Reval() is used to reshape the array created. Then, the model classifies the data using predict() by passing the symptoms to predict the diseases.

```
# Traning random forest model
mod = RandomForestClassifier(n_estimators = 100,n_jobs = 5, criterion= 'entropy',random_state = 42)
mod = mod.fit(x_train,y_train.values.ravel())
pred = mod.predict(x_test)
```

Performance

THE MODEL HAS AN ACCURACY OF 100%

Using metrics.accuracy_score() to calculate the accuracy, we get 100%

Accuracy

```
metrics.accuracy_score(y_test, pred)
```

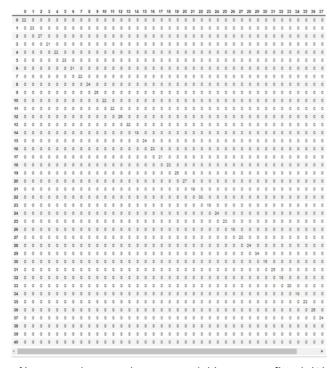
1.0

We then used classification_report() to check the precision (ration of true positive to the sum of true and false positive), recall (ratio of true positive to the sum of true positive and false negative), f1-score (weighted mean of precision and recall, the closer to 1 the better expected performance) and support (number of occurrences of the class in the dataset).

report = classification_report(y_test, pred, output_dict=True)
pd.DataFrame(report).transpose()

	precision	recall	f1-score	support					
(vertigo) Paroymsal Positional Vertigo	1.0	1.0	1.0	27.0	Hepatitis D	1.0	1.0	1.0	20.0
AIDS	1.0	1.0	1.0	13.0	Hepatitis E	1.0	1.0	1.0	24.0
Acne	1.0	1.0	1.0	25.0	Hypertension	1.0	1.0	1.0	22.0
Alcoholic hepatitis	1.0	1.0	1.0	20.0	Hyperthyroidism	1.0	1.0	1.0	26.0
Allergy	1.0	1.0	1.0	28.0	Hypoglycemia	1.0	1.0	1.0	28.0
Arthritis	1.0	1.0	1.0	28.0	Hypothyroidism	1.0	1.0	1.0	28.0
Bronchial Asthma	1.0	1.0	1.0	21.0	Impetigo	1.0	1.0	1.0	30.0
Cervical spondylosis	1.0	1.0	1.0	27.0	Jaundice	1.0	1.0	1.0	24.0
Chicken pox	1.0	1.0	1.0	17.0	Malaria	1.0	1.0	1.0	25.0
Chronic cholestasis	1.0	1.0	1.0	28.0	Migraine	1.0	1.0	1.0	27.0
Common Cold	1.0	1.0	1.0	26.0	Osteoarthristis	1.0	1.0	1.0	26.0
Dengue	1.0	1.0	1.0	23.0	Paralysis (brain hemorrhage)	1.0	1.0	1.0	25.0
Diabetes	1.0	1.0	1.0	32.0	Peptic ulcer diseae	1.0	1.0	1.0	22.0
Dimorphic hemmorhoids(piles)	1.0	1.0	1.0	23.0	Pneumonia	1.0	1.0	1.0	24.0
Drug Reaction	1.0	1.0	1.0	28.0	Psoriasis	1.0	1.0	1.0	27.0
Fungal infection	1.0	1.0	1.0	18.0	Tuberculosis	1.0	1.0	1.0	22.0
GERD	1.0	1.0	1.0	20.0	Typhoid	1.0	1.0	1.0	24.0
Gastroenteritis	1.0	1.0	1.0	22.0	Urinary tract infection	1.0	1.0	1.0	24.0
					Varicose veins	1.0	1.0	1.0	21.0
Heart attack	1.0	1.0	1.0	21.0	hepatitis A	1.0	1.0	1.0	28.0
Hepatitis B	1.0	1.0	1.0	26.0	accuracy	1.0	1.0	1.0	1.0
Hepatitis C	1.0	1.0	1.0	14.0	macro avg	1.0	1.0	1.0	984.0
					weighted avg	1.0	1.0	1.0	984.0

Performance



Confusion Matrix

```
cm = confusion_matrix(y_test, pred)
pd.DataFrame(cm)
```

This is a sample view of the matrix. A full one will be provided in the Appendix.

Now to make sure that our model is not overfitted. We used the model on the testing symptoms and compared the actual values to the predicted ones. We can see that all predictions are correct. Unlike the decision tree classification model shown in the appendx.

```
test = test.join(pd.DataFrame(mod.predict(C),columns=["predicted"]))[["prognosis","predicted"]]

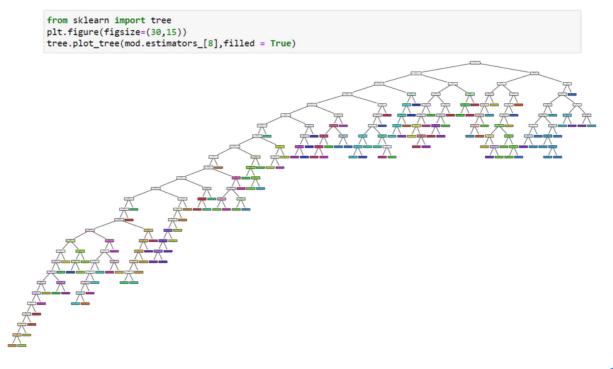
test['result']= ' '
for i in range(len(test)):
    if test["prognosis"][i] == test["predicted"][i]:
        test['result'].iloc[i] = 'Correct'
    else:
        test['result'].iloc[i] = 'Incorrect'
```

	prognosis	predicted	result
0	Fungal infection	Fungal infection	Correct
1	Allergy	Allergy	Correct
2	GERD	GERD	Correct
3	Chronic cholestasis	Chronic cholestasis	Correct
4	Drug Reaction	Drug Reaction	Correct
5	Peptic ulcer diseae	Peptic ulcer diseae	Correct
6	AIDS	AIDS	Correct
7	Diabetes	Diabetes	Correct
8	Gastroenteritis	Gastroenteritis	Correct
9	Bronchial Asthma	Bronchial Asthma	Correct
10	Hypertension	Hypertension	Correct
11	Migraine	Migraine	Correct
12	Cervical spondylosis	Cervical spondylosis	Correct
13	Paralysis (brain hemorrhage)	Paralysis (brain hemorrhage)	Correct
14	Jaundice	Jaundice	Correct
15	Malaria	Malaria	Correct
16	Chicken pox	Chicken pox	Correct
17	Dengue	Dengue	Correct

Performance

18	Typhoid	Typhoid	Correct
19	hepatitis A	hepatitis A	Correct
20	Hepatitis B	Hepatitis B	Correct
21	Hepatitis C	Hepatitis C	Correct
22	Hepatitis D	Hepatitis D	Correct
23	Hepatitis E	Hepatitis E	Correct
24	Alcoholic hepatitis	Alcoholic hepatitis	Correct
25	Tuberculosis	Tuberculosis	Correct
26	Common Cold	Common Cold	Correct
27	Pneumonia	Pneumonia	Correct
28	Dimorphic hemmorhoids(piles)	Dimorphic hemmorhoids(piles)	Correct
29	Heart attack	Heart attack	Correct
30	Varicose veins	Varicose veins	Correct
31	Hypothyroidism	Hypothyroidism	Correct
32	Hyperthyroidism	Hyperthyroidism	Correct
33	Hypoglycemia	Hypoglycemia	Correct
34	Osteoarthristis	Osteoarthristis	Correct
35	Arthritis	Arthritis	Correct
36	(vertigo) Paroymsal Positional Vertigo	(vertigo) Paroymsal Positional Vertigo	Correct
37	Acne	Acne	Correct
38	Urinary tract infection	Urinary tract infection	Correct
39	Psoriasis	Psoriasis	Correct
40	Impetigo	Impetigo	Correct
41	Fungal infection	Fungal infection	Correct

Here is a display of one of the decision trees in the forest. We have randomly chosen the tree at index 8:



Conclusion

The main aim of this disease prediction model is to predict the disease based on symptoms This model takes the symptoms of the user from which he or she suffers as input and generates the final output as a prediction of disease. In conclusion, for disease risk modeling, the accuracy of risk prediction depends on the diverse feature of the Health centers' data. Findings may help inform future developers of Disease Predictability Software and promote personalized patient care. The model predicts Patient Diseases through the Random Forest algorithm. Model accuracy reaches 100%. Machine learning skills are designed for Disease Prediction successfully





Resources

https://www.kaggle.com/datasets/kaushil268/disease-prediction-using-machine-learning

sklearn.ensemble.RandomForestClassifier — scikit-learn 1.2.1 documentation

Random Forest Classifier using Scikit-learn - GeeksforGeeks

https://www.ijraset.com/research-paper/disease-prediction-using-ml

Random Forest Classifier: Overview, How Does it Work, Pros & Cons | upGrad blog

Random Forest Classifier in Python Sklearn with Example - MLK - Machine Learning Knowledge

Sklearn metrics for Machine Learning in Python - Machine Learning HD



Comparision of actual data and predicted values of decision tree classification model:

Import Data

```
train = pd.read_csv('Dataset/Training.csv')
test = pd.read_csv('Dataset/Testing.csv')
```

Split Data

```
A = train[["prognosis"]] #diseases
B = train.drop(["prognosis"],axis=1) #symptoms
C = test.drop(["prognosis"],axis=1) #testing - symptoms
x_train, x_test, y_train, y_test = train_test_split(B,A,test_size=0.2)
```

Model

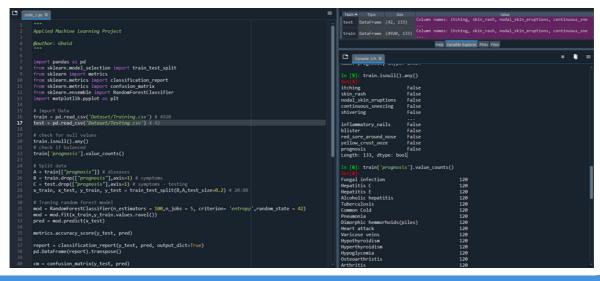
```
mod = DecisionTreeClassifier()
mod = mod.fit(x_train,y_train)
pred = mod.predict(x_test)
```

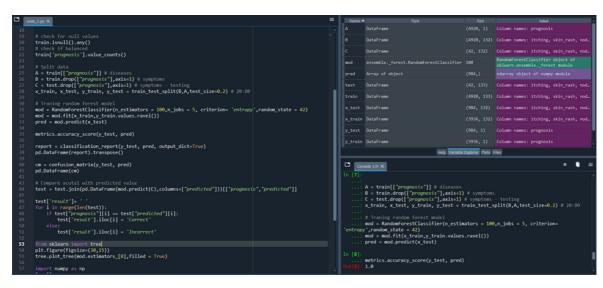
```
test = test.join(pd.DataFrame(mod.predict(C),columns=["predicted"]))[["prognosis","predicted"]]

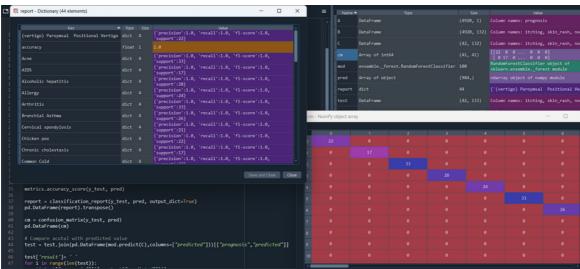
test['result']= ' '
for i in range(len(test)):
    if test["prognosis"][i] == test["predicted"][i]:
        test['result'].iloc[i] = 'Correct'
    else:
        test['result'].iloc[i] = 'Incorrect'
```

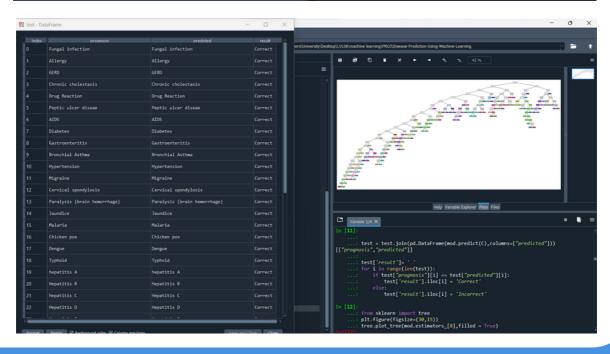
	prognosis	predicted	result
0	Fungal infection	Fungal infection	Correct
1	Allergy	Allergy	Correct
2	GERD	GERD	Correct
3	Chronic cholestasis	Chronic cholestasis	Correct
4	Drug Reaction	Drug Reaction	Correct
5	Peptic ulcer diseae	Peptic ulcer diseae	Correct
6	AIDS	AIDS	Correct
7	Diabetes	Diabetes	Correct
8	Gastroenteritis	Gastroenteritis	Correct
9	Bronchial Asthma	Bronchial Asthma	Correct
10	Hypertension	Hypertension	Correct
11	Migraine	Migraine	Correct
12	Cervical spondylosis	Cervical spondylosis	Correct
13	Paralysis (brain hemorrhage)	Paralysis (brain hemorrhage)	Correct
14	Jaundice	Jaundice	Correct
15	Malaria	Malaria	Correct
16	Chicken pox	Chicken pox	Correct

17	Dengue	Dengue	Correct
18	Typhoid	Typhoid	Correct
19	hepatitis A	hepatitis A	Correct
20	Hepatitis B	Hepatitis B	Correct
21	Hepatitis C	Hepatitis C	Correct
22	Hepatitis D	Hepatitis D	Correct
23	Hepatitis E	Hepatitis E	Correct
24	Alcoholic hepatitis	Alcoholic hepatitis	Correct
25	Tuberculosis	Tuberculosis	Correct
26	Common Cold	Common Cold	Correct
27	Pneumonia	Pneumonia	Correct
28	Dimorphic hemmorhoids(piles)	Dimorphic hemmorhoids(piles)	Correct
29	Heart attack	Heart attack	Correct
30	Varicose veins	Varicose veins	Correct
31	Hypothyroidism	Hypothyroidism	Correct
32	Hyperthyroidism	Hyperthyroidism	Correct
33	Hypoglycemia	Hypoglycemia	Correct
34	Osteoarthristis	Osteoarthristis	Correct
35	Arthritis	Arthritis	Correct
36	(vertigo) Paroymsal Positional Vertigo	(vertigo) Paroymsal Positional Vertigo	Correct
37	Acne	Acne	Correct
38	Urinary tract infection	Urinary tract infection	Correct
39	Psoriasis	Psoriasis	Correct
40	Impetigo	Impetigo	Correct
41	Fungal infection	Impetigo	Incorrect









17

