Predicting Heart Diseases In Logistic Regression Of Machine Learning Algorithms By Python Jupyterlab

A. S. Thanuja Nishadi

University of Colombo, Faculty of Graduate Studies, Sri Lanka,
thanuja.nishadi@gmail.com

Abstract: Healthcare expenditures are overwhelming national and corporate budgets due to asymptomatic diseases including cardiovascular diseases. Therefore, there is an urgent need for early detection and treatment of such diseases. Machine learning is one of the trending technologies which used in many spheres around the world including healthcare industry for predicting diseases. The aim of this study is to identify the most significant predicators of heart diseases and predicting the overall risks by using logistic regression. Thus, binary logistic model which is one of the classification algorithms in machine learning is used in this study to identify thepredicators. Further, data analysis is carried out in Python using JupyterLab in order to validate the logistic regression.

Keywords: machine learning, logistic regression, classification algorithms, heart diseases

1. Introduction

The number of deaths due to cardiovascular diseases increased by 41% between 1990 and 2013, climbing from 12.3 million deaths to 17.3 million deaths in globally. In addition to that, half of the deaths in the United States and other developed countries are due to the same issue [1].Therefore, early detection of heart diseases is required to reduce the health complications. Machine learning has been widely used in modern healthcare sector for diagnosing and predicting the presence of diseases using data models. Logistic regression is one such relatively used machine learning algorithms for studies involving risk assessment of complex diseases. Thus, the study intends to identify the most significant predicators of cardiovascular diseases and predicting the overall risk by using logistic regression.

2. Background of the study

The dataset which used for the logistic regression analysis is available on the Kaggle website(https://www.kaggle.com), from an ongoing cardiovascular study of Framingham, Massachusetts. The classification goal of this study is to predict whether the patient has 10-year risk of future heart diseases. The Framingham dataset consists with 4238 records ofpatients'dataand15attributes.Thedataanalysisiscarried out in Python programming by using JupyterLab which is more flexible and powerful data science applicationsoftware.

3. Machine Learning (ML)

Machine learning is widely used in almost many fields in the world including healthcare sector. Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed [2]. Further, machine learning at its most basic is the practice of using algorithms to parse data, learn from it, and then make a determination or prediction about something in the world [3]. There are two major categories of problems often solved by machine learning i.e. regression and classification. Mainly, the regression algorithms are used for numeric data and classification problems include binary and multi-category problems [4].Machine learning algorithms are further divided into two categories such as supervised learning and unsupervised learning [5]. Basically, supervised learning is performed by using prior knowledge in output values whereas unsupervised learning does not predefined labels hence the goal of this is to infer the natural structures within the dataset [6]. Therefore, selection of machine learning algorithm need to carefully evaluated.

4. Logistic Regression Model

Logistic regression is a one of the machine learning classification algorithm for analyzing a dataset in which there are one or more independent variables (IVs) that determine an outcome and also categorical dependent variable (DV)[7]. Linear regression uses output in continuous numeric whereas logistic regression transforms its output using the logistic sigmoid function to return a probability value which can then be mapped to two or more discrete classes [8]. The logistics regression forms three types as below.

- **a)** Binary logistics regression (two possible outcomes in a DV)
- **b)** Multinomial logistics regression (three or more categories in DV without ordering)
- **c)** Ordinal logistics regression (three or more categories in DV with ordering) [9]

Furthermore, logistic regression model uses more complex costfunction (knownassigmoidfunctionorlogisticfunction) instead of linear function[10]. Logistic regression limits the cost function between 0 and1.

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

Sigmoid Function

In the formula, σ(z)= output between 0 and 1 (probability estimate), z = input to the function and e = base of natural log.

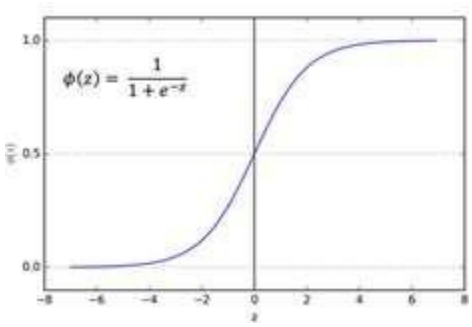


Figure 1: *Logistic Regression*

According to the given data set, 1 indicates the high risk of 10-year future coronary heart disease and 0 indicates non or no heart risks. The independent variables n in the logistic model as x1, x2, x3……., xn

$$\log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \ldots\ldots\ldots\ldots + \beta_n x_n$$

Logisticregressionachievesthisbytakingthelogoddsofthe event ln(P/1−P), where, P is the probability of event which is risk of CHD. Therefore, P always lies between 0 and1.

5. Methodology

5.1 Workflow of Machine Learning ModelBuilding

Figure 2 indicates the steps followed in order to build the logistic regression model in machine learning.

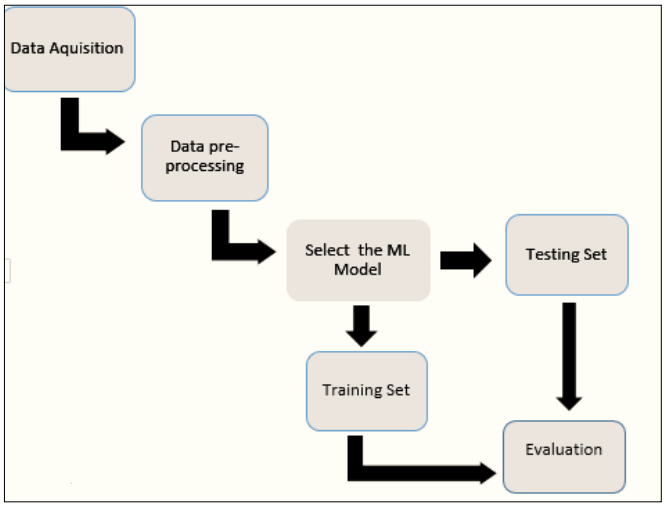


Figure 2: *Workflow of Logistic Regression Model*

5.1.1 Data Acquisition

The dataset is collected from Kaggle website.

5.1.2 Data Pre-Processing

In order to build up more accurate ML model, data pre-processing is required. Data pre-process is the process of cleaning the data. This includes identification of missing data, noisy data and inconsistent data.

5.1.3 Select Machine LearningModel

The pre-processed data are identified using machine learning algorithms.

a) Input Variables of the study

The data set consists with 14 IVS and predicted value. ML model is based on identification of DV. It has used binary logistic regression which is one of the classification algorithms due to target variable is categorical.

Table 1: *Input Variables*

Variable Category	Variable Name	Description	Data Type
Demographic	Sex	Male or female	Nominal
	age	Age of the patient	Continuous
Behavior	currentSmoker	Current smoker or not?	Nominal
	cigsPerDay	Cigarettes per day?	Continuous
Medical History	BPMeds	Blood pressuremedication?	Nominal
	prevalentStroke	Whether previously had stroke?	Nominal
	prevalentHyp	Whether was hypertensive?	Nominal
	diabetes	Whether had diabetes?	Nominal
Current Medical Status	totChol	Total Cholesterol Level	Continuous
	sysBP	Systolic Blood Pressure	Continuous
	diaBP	Diastolic Blood Pressure	Continuous
	BMI	Body Mass Index	Continuous
	heartRate	Heart Rate	Continuous
	glucose	Glucose Level	Continuous
Predicted Variable	TenYearCHD	10-year risk of CHD	Binary

6. Data Analysis

Data Analysis was carried out using Jupyter Lab using Python. The following steps were implemented in order to process the logistics regression.

6.1 Loading Data and Other Required Libraries

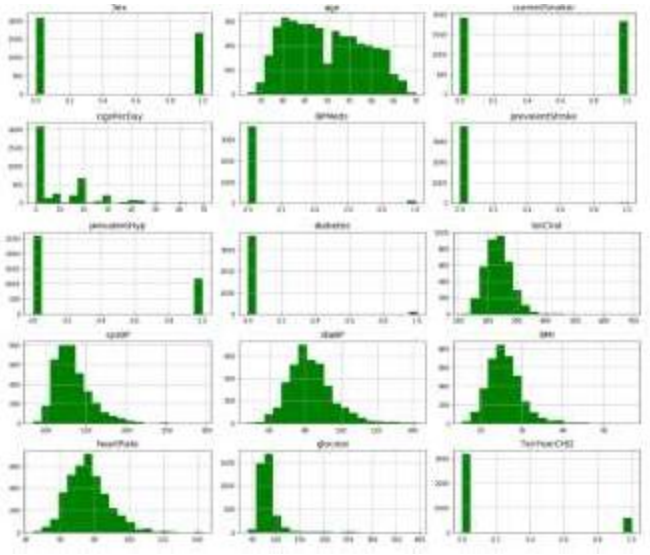
It has loaded the heart prediction data using Framingham CSV file into Jupiter Lab in Order to build the logistic regression model. In addition to that, required libraries which used as supportive applications are loaded. It has removed the education field from the database.

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import scipy.stats as st
import matplotlib.pyplot as plt
import seaborn as sn
from sklearn.metrics import confusion_matrix
import matplotlib.mlab as mlab
%matplotlib inline
```

```
heartdb=pd.read_csv("C:\\Users\\LAB-User\\Desktop\\framingham.csv")
heartdb.drop(['education'],axis=1,inplace=True)
heartdb.head()
```

6.2 Exploratory Data Analysis(EDA):

The following visualization derived through the JupyterLab for displaypredicators.



6.3 Identify Missing Values

Further, the number of missing values has identified for cleaning existing dataset. The summarized total number of missing values based on the attributes are given below.

```
In [5]: heartdb.isnull().sum()

Out[5]: Sex                0
        age                0
        currentSmoker      0
        cigsPerDay        29
        BPMeds            53
        prevalentStroke    0
        prevalentHyp       0
        diabetes           0
        totChol           50
        sysBP              0
        diaBP              0
        BMI               19
        heartRate          1
        glucose          388
        TenYearCHD         0
        dtype: int64
```

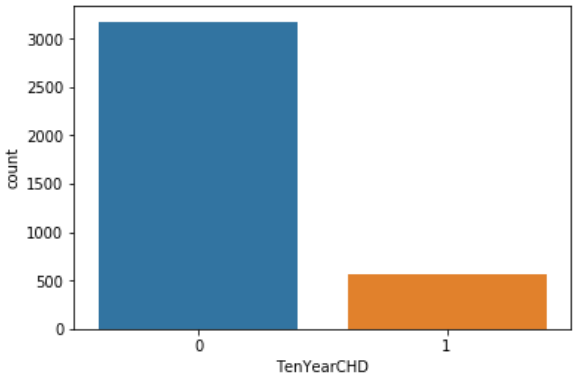
Then, the total percentage of missing values in column was identified using Pandas Data Frame. Total number of rows with missing values is 489 since it is only 12 percent of the entire dataset the rows with missing values are excluded. It has used Pandas dropna() method which was used to analyze the drop rows/columns with Null values.

```
In [7]: heartdb.dropna(axis=0,inplace=True)
```

The descriptive figures related to 10year risk of CHD has indicated below.

```
In [9]: heartdb.TenYearCHD.value_counts()

Out[9]: 0    3177
        1     572
        Name: TenYearCHD, dtype: int64
```

```
sn.countplot(x='TenYearCHD',data=heartdb)

<matplotlib.axes._subplots.AxesSubplot at 0x1fe5aa6ea90>
```



According to the above data, there are 3179 patents with no heart disease and 572 patients with risk of heart disease.

6.4 Implementing Logistic Regression

The following outcomes are used to indicate the logistic regression. Logistic regression is mainly used to for prediction and also calculating the probability of success.

Logit Regression Results

Dep. Variable:	TenYearCHD	**No. Observations:**	3749
Model:	Logit	**Df Residuals:**	3734
Method:	MLE	**Df Model:**	14
Date:	Mon, 17 Jun 2019	**Pseudo R-squ.:**	0.1169
Time:	14:52:40	**Log-Likelihood:**	-1414.1
converged:	True	**LL-Null:**	-1601.4
		LLR p-value:	2.922e-71

	coef	std err	z	P>|z|	[0.025	0.975]
const	-8.6463	0.687	-12.577	0.000	-9.994	-7.299
Sex	0.5740	0.107	5.343	0.000	0.363	0.785
age	0.0640	0.007	9.787	0.000	0.051	0.077
currentSmoker	0.0732	0.155	0.473	0.636	-0.230	0.376
cigsPerDay	0.0184	0.006	3.003	0.003	0.006	0.030
BPMeds	0.1446	0.232	0.622	0.534	-0.311	0.600
prevalentStroke	0.7191	0.489	1.471	0.141	-0.239	1.677
prevalentHyp	0.2146	0.136	1.574	0.116	-0.053	0.482
diabetes	0.0025	0.312	0.008	0.994	-0.609	0.614
totChol	0.0022	0.001	2.074	0.038	0.000	0.004
sysBP	0.0153	0.004	4.080	0.000	0.008	0.023
diaBP	-0.0039	0.006	-0.619	0.536	-0.016	0.009
BMI	0.0103	0.013	0.820	0.412	-0.014	0.035
heartRate	-0.0023	0.004	-0.550	0.583	-0.010	0.006
glucose	0.0076	0.002	3.408	0.001	0.003	0.012

According to the above logistic results P >= 0.05 show low statistically significance relationship with probability of heart disease. Therefore, backward elimination approach has been used to remove the attributes with highest P values. The process will be continued until all the attributes of P values less than 0.05.

Logit Regression Results

Dep. Variable:	TenYearCHD	**No. Observations:**	3749
Model:	Logit	**Df Residuals:**	3742
Method:	MLE	**Df Model:**	6
Date:	Mon, 17 Jun 2019	**Pseudo R-squ.:**	0.1148
Time:	14:53:21	**Log-Likelihood:**	-1417.6
converged:	True	**LL-Null:**	-1601.4
		LLR p-value:	2.548e-76

	coef	std err	z	P>|z|	[0.025	0.975]
const	-9.1211	0.468	-19.491	0.000	-10.038	-8.204
Sex	0.5813	0.105	5.521	0.000	0.375	0.788
age	0.0654	0.006	10.330	0.000	0.053	0.078
cigsPerDay	0.0197	0.004	4.803	0.000	0.012	0.028
totChol	0.0023	0.001	2.099	0.036	0.000	0.004
sysBP	0.0174	0.002	8.166	0.000	0.013	0.022
glucose	0.0076	0.002	4.573	0.000	0.004	0.011

The above output indicates the result after using backward elimination. The logistic regression equation for the heart prediction data as follows.

$$\text{logit(P)} = \log\left(\frac{\text{P}}{1-\text{P}}\right) = \beta_0 + \beta_1 * \text{Sex} + \beta_2 * \text{age} + \beta_3 * \text{cigsPerDay} + \beta_4 * \text{totChol} + \beta_5 * \text{sysBP} + \beta_6 * \text{glucose}$$

6.5 Interpreting Logistic Results

The following methods indicates the accuracy measurements.

a) Interpreting Odds Ratio(OR):

This is used to measure the association between an exposure with outcome. Further, the odds ratio can also be used to determine whether a particular exposure is a risk factor for a particular outcome, and to compare the magnitude of various risk factors for that outcome.

- OR=1 Exposure does not affect odds of outcome
- OR>1 Exposure associated with higher odds of outcome
- OR<1 Exposure associated with lower odds of outcome

b) Confidence Intervals(CI):

The accuracy of OR is estimated by using 95% confidence interval (CI). A large CI represents the low level of precision of OR and also small CI represents the higher precision of OR. However, 95% CI does not indicate the statistical significance unlike the p value.

	CI 95%(2.5%)	CI 95%(97.5%)	Odds Ratio	pvalue
const	0.000044	0.000274	0.000109	0.000
Sex	1.454877	2.198166	1.788313	0.000
age	1.054409	1.080897	1.067571	0.000
cigsPerDay	1.011730	1.028128	1.019896	0.000
totChol	1.000150	1.004386	1.002266	0.036
sysBP	1.013299	1.021791	1.017536	0.000
glucose	1.004343	1.010895	1.007614	0.000

- According to the fitted model, the odds of diagnosed with heart disease of males (78.8%) is higher than the females.
- Further, the odds of diagnosis with CHD is increase approximately 7% for a one-year age increase (1.067571)
- In addition to that, additional cigarette has risk of 2% increase in odds of CHD.
- Furthermore, odds of sysBP has 1.7% increase in every unit increase.
- No significance changes in the total cholesterol level and glucose level.

6.6 Training and testing sets

Data set was separated into training and testing sets for evaluation process. This has been done using scikit-learn library.

```
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression()
logreg.fit(x_train,y_train)
y_pred=logreg.predict(x_test)
```

```
sklearn.metrics.accuracy_score(y_test,y_pred)
```

```
0.8666666666666667
```

The accuracy of the model is 0.87.

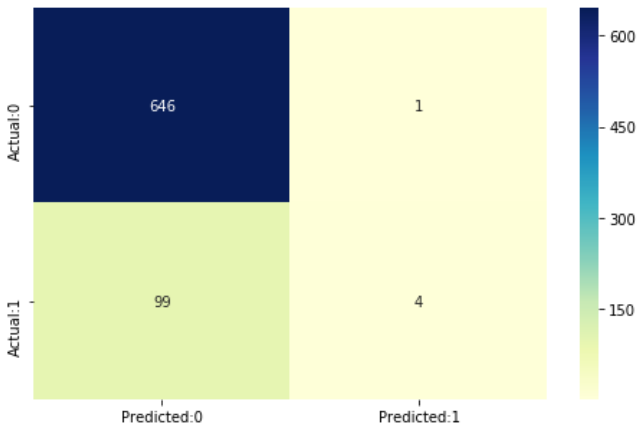
6.7 Confusion Matrix Outcomes

This has used to indicate the summary of prediction results including correct and incorrect on a classification problem. Further, this was used to not only errors but also types of errors. The segments of the confusion matrix indicate the following parameters.

- **True Positives (TP):** cases which are predicted yes (they have the disease), and they do have the disease.
- **True Negatives (TN):** cases which are predicted no, and they do not have the disease.
- **False Positives (FP):** cases which are predicted yes, but they do not actually have the disease (Type I error).
- **False Negatives (FN):** cases which are predicted no, but they actually do have the disease (Type II error).

The following outcome indicates the confusion matrix of the dataset.

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fe7f479e10>
```



According to the outcome of the confusion matrix,
Correct predictions (646+4) =650
Incorrect predictions (99+1) =100

Therefore,
True Positives:4
True Negatives:646
False Positives:1(Type I error)
False Negatives:99(Type II error)

```
TN=cm[0,0]
TP=cm[1,1]
FN=cm[1,0]
FP=cm[0,1]
sensitivity=TP/float(TP+FN)
specificity=TN/float(TN+FP)
```

This is a list of rates that are often computed from a confusion matrix for a binary classifier:

It has been checked the accuracy of the model using confusion matrix.

Terms	Formula
Accuracy of the model (overall, how often the classifer correct)	(TP+TN)/(TP+TN+FP+FN)
Misclassification Rate (overall, how often it wrong or error rate)	(FP+FN)/(TP+TN+FP+FN)
Sensitivity or True Positive Rate (when it is actually yes, how often does it predict yes)	TP/(TP+FN)
Specificity or True Negative Rate (when it is actually no, how often does it predict no)	TN/(TN+FP)

```
The accuracy of the model = TP+TN/(TP+TN+FP+FN) =  0.8666666666666667
The Misclassification = 1-Accuracy =  0.1333333333333333
Sensitivity or True Positive Rate = TP/(TP+FN) =  0.038834951456310676
Specificity or True Negative Rate = TN/(TN+FP) =  0.9984544049459042
Positive Predictive value = TP/(TP+FP) =  0.8
Negative predictive Value = TN/(TN+FN) =  0.8671140939597315
Positive Likelihood Ratio = Sensitivity/(1-Specificity) =  25.126213592233354
Negative likelihood Ratio = (1-Sensitivity)/Specificity =  0.962059201358622
```

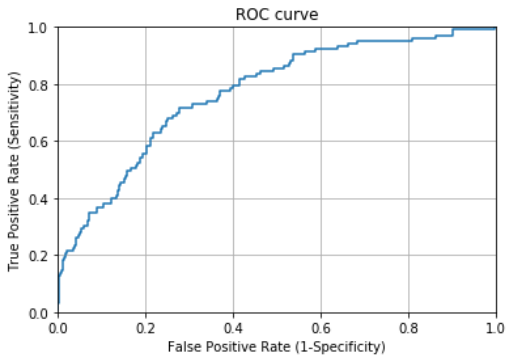
With analyzing confusion matrix data, it is evident that the model is highly specific than sensitive. Further, the negative values in the model are predicted more accurately than the positives.

```
With 0.1 threshold the Confusion Matrix is
 [[242 405]
 [  8  95]]
 with 337 correct predictions and 8 Type II errors( False Negatives)

 Sensitivity:  0.9223300970873787 Specificity:  0.3740340030911901

With 0.2 threshold the Confusion Matrix is
 [[513 134]
 [ 43  60]]
 with 573 correct predictions and 43 Type II errors( False Negatives)

 Sensitivity:  0.5825242718446602 Specificity:  0.7928902627511591

With 0.3 threshold the Confusion Matrix is
 [[615  32]
 [ 75  28]]
 with 643 correct predictions and 75 Type II errors( False Negatives)

 Sensitivity:  0.27184466019417475 Specificity:  0.9505409582689336

With 0.4 threshold the Confusion Matrix is
 [[643   4]
 [ 90  13]]
 with 656 correct predictions and 90 Type II errors( False Negatives)

 Sensitivity:  0.1262135922330097 Specificity:  0.9938176197836167
```

```
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob_yes[:,1])
plt.plot(fpr,tpr)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.title('ROC curve')
plt.xlabel('False Positive Rate (1-Specificity)')
plt.ylabel('True Positive Rate (Sensitivity)')
plt.grid(True)
```

6.8 ROC Curve

The ROC Curve is a simple plot which used to visualize the performance of a binary classifier. Further, this shows the tradeoff between the true positive rate and the false positive rate of a classifier for various choices of the probability threshold.



Good classification accuracy models should have significantly more true positives than the false positives at all thresholds. Area Under the Curve(AUC) quantifies the model classification accuracy.

7. Conclusion

The aim of this study is to evaluate the risk of 10-year CHD using 14 IVs. The attributes are selected after the backward elimination process considering the P values which are lower than 5%. Therefore, the logistic regression model is derived through P values of the variables <0.05 (sex, age, cigsPerDay, totChol, sysBP, glucose). According to the logistic regression outcome, men are more suspectable to heart disease than women. Age, number of cigarettes per day and systolic blood pressure are the odds of CHD. However, There is no significance change in the total cholesterol level and the glucose level. But, the level of glucose has a negligible change in odds. The model is more specific than sensitive. Further, the accuracy of the moel is 0.87. The value under the ROC curve is 73.5which is somewhat satisfactory. Moreover, the model could be improved by using more data.

References

[1]. Mozaffarian, D., Benjamin, E., Go, A., Arnett, D., Blaha, M.Cushman, M. et al. (2015). Heart Disease and Stroke Statistics—2015, Update. Circulation, 131(4). doi: 10.1161/cir.0000000000000152.

[2]. Das, S., Dey, A., Pal, A., & Roy, N. (2015). Applications of Artificial Intelligence in Machine Learning: Review and Prospect. International Journal of Computer Applications, 115(9), 31-41. doi: 10.5120/20182-2402

[3]. Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. (2019). Applications of Artificial Intelligence in Transport: An Overview. Sustainability, 11(1), 189. doi: 10.3390/su11010189

[4]. Strecht, Pedro & Cruz, Luís & Soares, Carlos & Moreira, João & Abreu, Rui. (2015). A Comparative Study of Classification and Regression Algorithms for Modelling Students' Academic Performance, , https://www.researchgate.net/publication/278030689_A_Comparative_Study_of_Classification_and_Regression_Algorithms_for_Modelling_Students'_Academic_Performance, viewed: 10th June 2019.

[5]. Sathya, R & Abraham, A (2013) International Journal of Advanced Research in Artificial Intelligence, Vol. 2, No. 2, 2013, http://ijarai.thesai.org/Downloads/IJARAI/Volume2No2/Paper_6-Comparison_of_Supervised_and_Unsupervised_Learning_Algorithms_for_Pattern_Classification.pdf, viewed: 10th June 2019.

[6]. CVA, K. (2017), https://www.medwinpublishers.com/JOBD/JOBD16000139.pdf. Journal of Orthopedics & Bone Disorders, 1(7). doi: 10.23880/jobd-16000139

[7]. Miguel-Hurtado, O., Guest, R., Stevenage, S., Neil, G., & Black, S. (2016). Comparing Machine Learning Classifiers and Linear/Logistic Regression to Explore the Relationship between Hand Dimensions and Demographic Characteristics. PLOS ONE, 11(11), e0165521. doi: 10.1371/journal.pone.0165521

[8]. Ng, A. Y. and Jordan, M. I. (2002). On discriminative vs. generative classifiers: A comparison of logistic regression and naive bayes. In NIPS 14, pp. 841–848.

[9]. Peng, C., Lee, K., & Ingersoll, G. (2002). An Introduction to Logistic Regression Analysis and Reporting. The Journal of Educational Research, 96(1), 3-14. doi: 10.1080/00220670209598786

[10]. Park, H. (2019). An Introduction to Logistic Regression: From Basic Concepts to Interpretation with Particular Attention to NursingDomain, https://pdfs.semanticscholar.org/3305/2b1d2363aee3ad290612109dcea0aed2a89e.pdf, viewed : 10th June 2019