





# Orthopedic classification.

Machine Learning Project.

# Team members:

Sherif Ashraf Ahmed Roshdy.

Abdelrahman Mohamed Khalil.

Mohamed Hosny Mosad.

Yahia Zakria Ebrahim.

Sobeh Salah Sobeh.



#### Introduction.

Domain of problem. Software Details and Project Objective.

#### Dataset.

Information about dataset. Exploratory Dataset.

#### The Algorithms used to classification

Data preprocessing for machine learning.
KNN, Naive Bayes classifiers, Decision tree classifier.

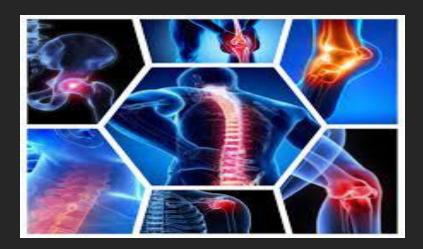
#### Conclusion.

Compare with accurse of each model. the decision of solving problem.

#### Introduction

Domain of problem.

• Orthopedic relating to the branch of medicine dealing with the correction of deformities of bones or muscles.





#### Introduction

Conn.

- If you suffer from pain in the bones, the bone examination will show whether this pain is normal or abnormal.
- This is important because, in the event of abnormal pain, you will have to go to a specialist.

  After all, it may be very dangerous, such as Joints Dislocation or Fractures.
- Bone, normal or abnormal, is an important tool for detecting cancer spread in the bones from the site of the original tumor, such as breast or prostate cancer,
- It helps in repairing and preventing deformities in children at an early stage, and these deformities result from some factors that may affect the body while it is still at the embryo stage.

#### Introduction

Software Details and Project Objective.



#### Software Details:

Python (libraries) >> Pandas, SKLearn, Seaborn, Matplotlib, numpy.

Dataset >> Kaggle.



#### **Project Objective**

Used machine learning algorithms to classify a patient's condition as normal or abnormal based on various orthopedic parameters

Biomechanical features of orthopedic patients | Kaggle



Information about dataset

Biomechanical features of orthopedic patients

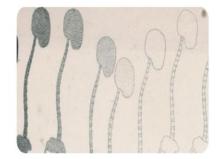






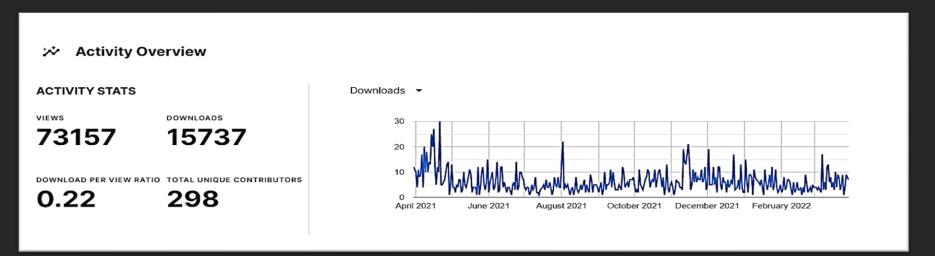
# Biomechanical features of orthopedic patients

Classifying patients based on six features



Conn.

- The task consists in classifying patients as belonging to one out of two categories: Normal or Abnormal.
- Activity Overview of dataset



Conn.

Each patient is represented in the data set by six biomechanical attributes derived from the shape and orientation of the pelvis and lumbar spine (each one is a column)

lumbar grade of pelvic spondylolis Pelvic Iordosis sacral pelvic tilt radius incidence thesis slope angle إمالة الحوض نصف قطر منحدر عجزي در جة انزلاق حدوث الحوض زاوية قعس الحو ض قطني الفقار

Exploratory Dataset.

#### • Show the first 10 rows.

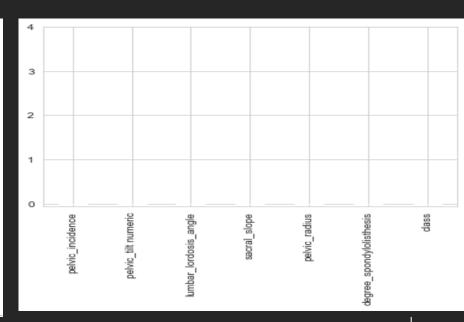
	pelvic_incidence	pelvic_tilt numeric	lumbar_lordosis_angle	sacral_slope	pelvic_radius	degree_spondylolisthesis	class
0	63.027817	22.552586	39.609117	40.475232	98.672917	-0.254400	Abnormal
1	39.056951	10.060991	25.015378	28.995960	114.405425	4.564259	Abnormal
2	68.832021	22.218482	50.092194	46.613539	105.985135	-3.530317	Abnormal
3	69.297008	24.652878	44.311238	44.644130	101.868495	11.211523	Abnormal
4	49.712859	9.652075	28.317406	40.060784	108.168725	7.918501	Abnormal
5	40.250200	13.921907	25.124950	26.328293	130.327871	2.230652	Abnormal
6	53.432928	15.864336	37.165934	37.568592	120.567523	5.988551	Abnormal
7	45.366754	10.755611	29.038349	34.611142	117.270067	-10.675871	Abnormal
8	43.790190	13.533753	42.690814	30.256437	125.002893	13.289018	Abnormal
9	36.686353	5.010884	41.948751	31.675469	84.241415	0.664437	Abnormal

Conn.

- Print a concise summary of a DataFrame.
- The shape >> (1180,7)

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1180 entries, 0 to 1179
Data columns (total 7 columns):
    Column
                             Non-Null Count Dtype
    pelvic_incidence
                       1180 non-null
                                           float64
    pelvic_tilt numeric 1180 non-null float64
    lumbar_lordosis_angle 1180 non-null float64
    sacral slope
                           1180 non-null float64
    pelvic radius
                            1180 non-null float64
    degree_spondylolisthesis 1180 non-null
                                          float64
    class
                                            object
                             1180 non-null
dtypes: float64(6), object(1)
memory usage: 64.7+ KB
```

#### Check the non-null values



Conn.

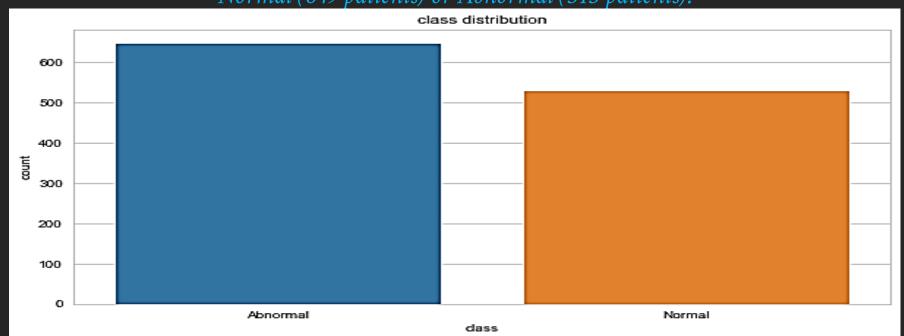
• Show <u>descriptive statistics</u> include those that summarize the central tendency, dispersion and shape of a dataset's distribution.

	pelvic_incidence	pelvic_tilt numeric	lumbar_lordosis_angle	sacral_slope	pelvic_radius	degree_spondylolisthesis
count	1180.000000	1180.000000	1180.000000	1180.000000	1180.000000	1180.000000
mean	60.628995	19.534941	42.966891	34.621027	115.654789	39.428121
std	12.212527	10.779453	21.270700	12.197810	14.427055	40.814087
min	26.147921	-6.554948	14.000000	13.366931	70.082575	-11.058179
25%	50.804924	12.537992	28.957819	25.065929	107.690466	11.400298
50%	61.542890	17.977784	38.926371	33.918037	116.250917	33.157646
75%	69.658921	24.822631	48.426306	43.163549	124.118877	55.995454
max	129.834041	49.431864	125.742385	121.429566	163.071041	418.543082

Conn.

Represent the number of output:

Normal (649 patients) or Abnormal (513 patients).



Conn.

• Plot <u>pairwise relationships</u> in a dataset using seaborn.pairplot function.



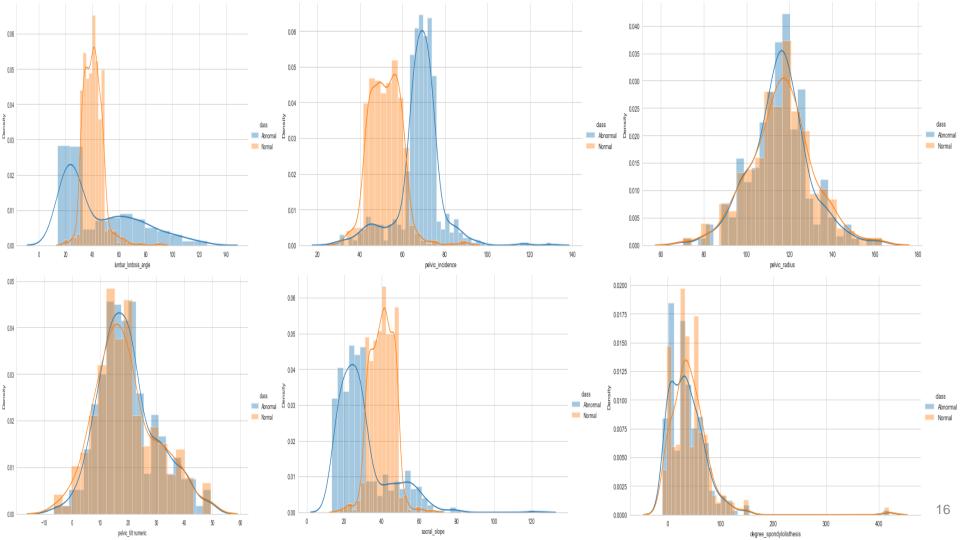
Conn.

• FacetGrid class helps in visualizing distribution of one

variable as well as the relationship between multiple

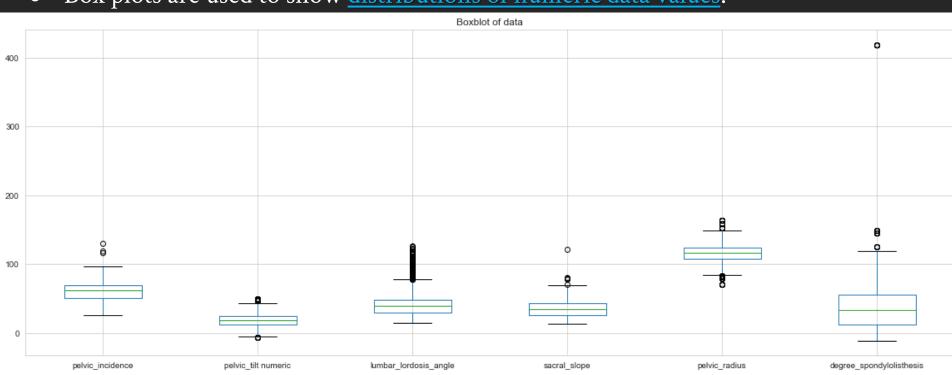
variables separately within subsets of your dataset using

multiple panels.



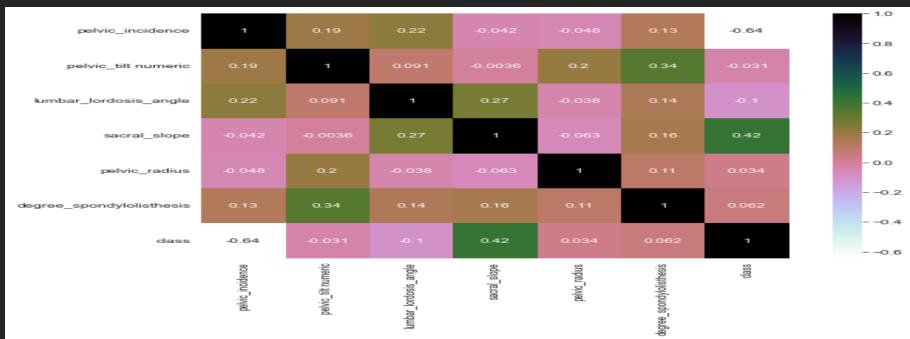
Conn.

• Box plots are used to show <u>distributions of numeric data values</u>.



Conn.

 Representing the correlation between features and some of them using heatmap function



# Data preprocessing for machine learning

Splitting dataset

#### Input data.

	pelvic incidence	nolvie tilt numorie	lumbar lordosis anglo	sacral clone	polyic radius	degree spondylolisthesis
	pervic_incluence	pervic_tilt ilumeric	idilibai_lordosis_angle	sacrai_stope	pervic_radius	degree_spondylonstriesis
0	63.027817	22.552586	39.609117	40.475232	98. <mark>672917</mark>	-0.254400
1	39.056951	10.060991	25.015378	28.995960	114.405425	4.564259
2	68.832021	22.218482	50.092194	46.613539	105.985135	-3.530317
3	69.297008	24.652878	44.311238	44.644130	101.868495	11.211523
4	49.712859	9.652075	28.317406	40.060784	108.168725	7.918501







#### Output data

```
data_output.head()

0      0

1      0

2      0

3      0

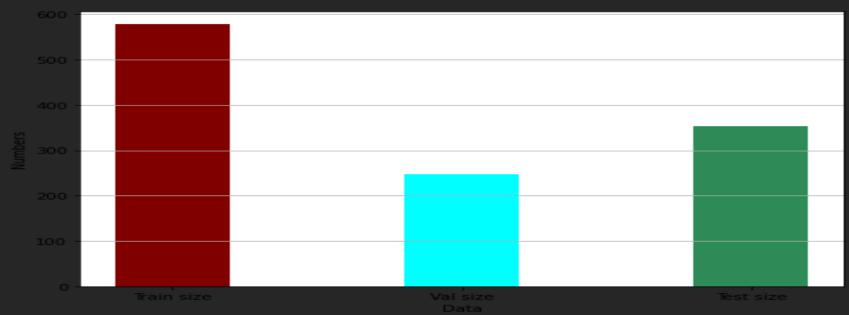
4      0

Name: class, dtype: int64
```

# Data preprocessing for machine learning

Splitting Datasets

• We need to split our dataset to 3 sets: Training, Validation, and Test data subsets.



X\_train: (578, 6) y\_train: (578,)



X\_val: (248, 6) y\_val: (248,)



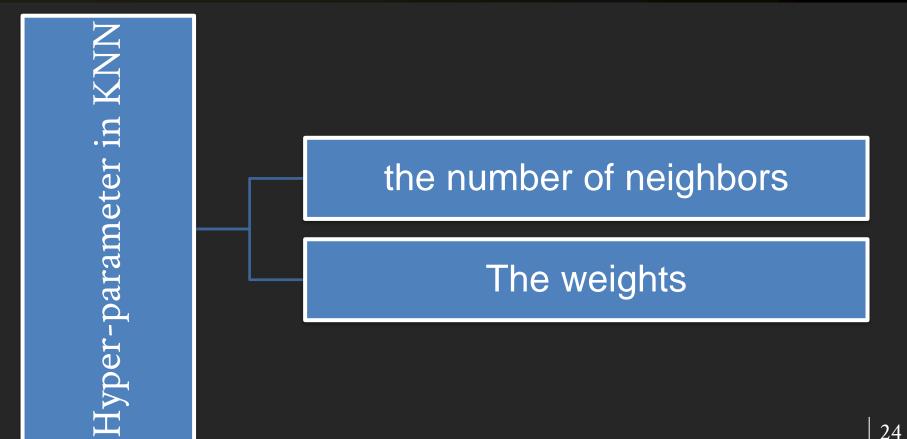
X\_test: (354, 6) y\_test: (354,)

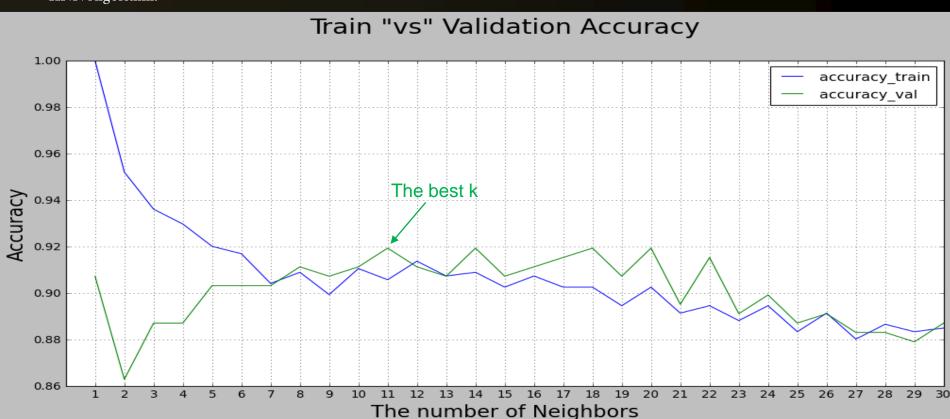
(KNN, Naive Bayes, Decision Tree)

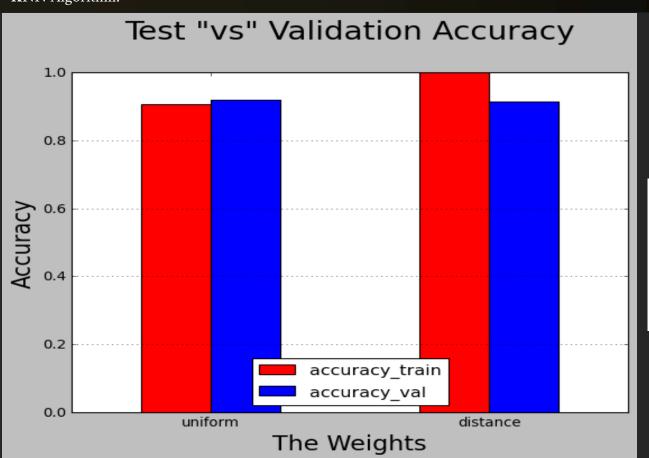


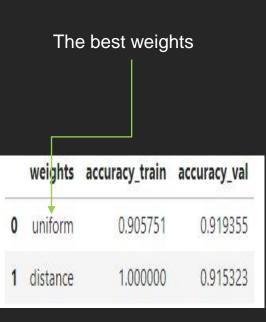
Hyper-parameter tuning

- When we build a machine learning model, we have a number of
   Hyper-parameters
   that will determine how our model looks like.
- Changing the values of these variables will affect the accuracy of our model.
- We need to find the best hyper-parameters for our model to achieve the best accuracy.









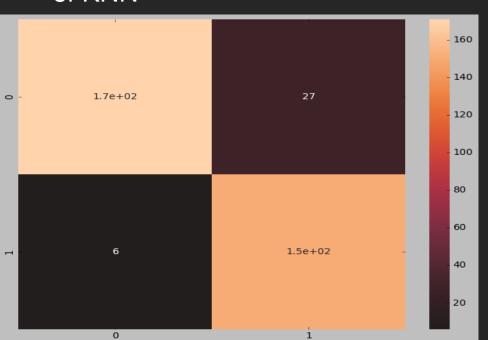
KNN Algorithm.

Then we applied the KNeighborsClassifier using the best K (11)
 ,weight="uniform"

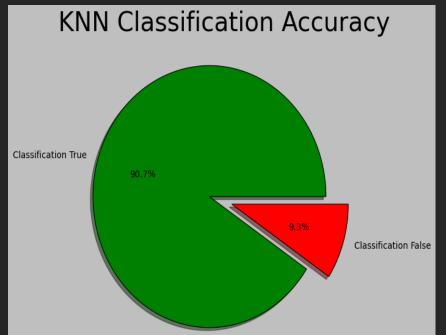
```
best_knn_model=KNeighborsClassifier(n_neighbors=11,weights='uniform')
best_knn_model.fit(X_train_balanced,y_train_balaned)
y_pred_test=best_knn_model.predict(X_test)
knn_acc_final=accuracy_score(y_test,y_pred_test)
print(round(knn_acc_final,3)*100,"%")
```

KNN Algorithm.

# plotted the confusion matrix of KNN

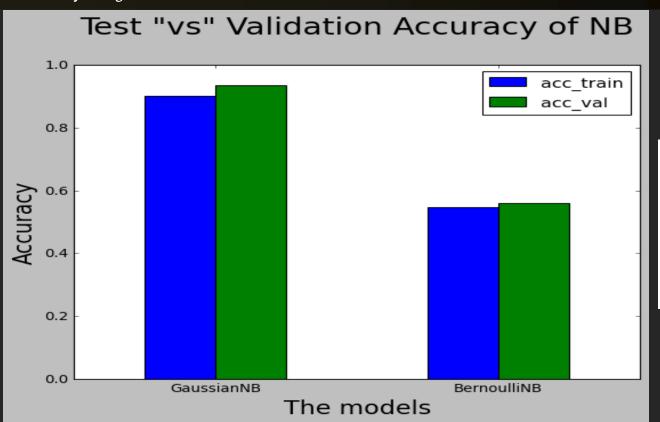


#### KNN Accuracy = 91%

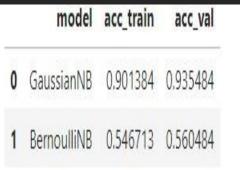


# Naive Bayes Algorithm.

Naive Bayes Algorithm.



# GaussianNB model win



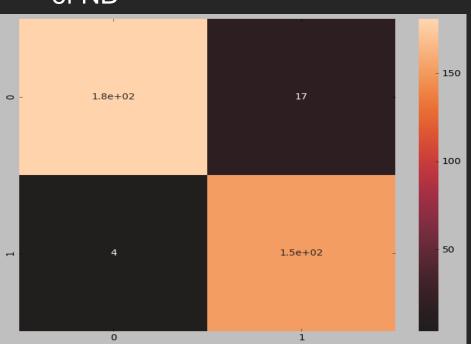
Naive Bayes Algorithm.

We applied GaussianNB() in the data

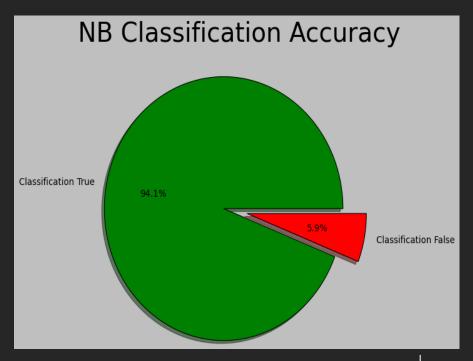
```
best_nb_model=GaussianNB()
best_nb_model.fit(X_train,y_train)
y_pred_test=best_nb_model.predict(X_test)
model_nb_final=accuracy_score(y_test,y_pred_test)
print(round(model_nb_final,3)*100,"%")
```

Naive Bayes Algorithm.

# plotted the confusion matrix of NB

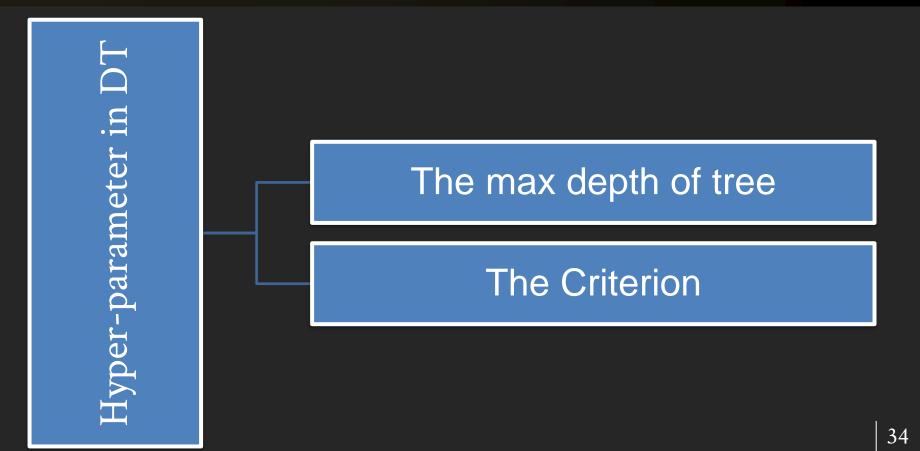


#### NB Accuracy = 94%



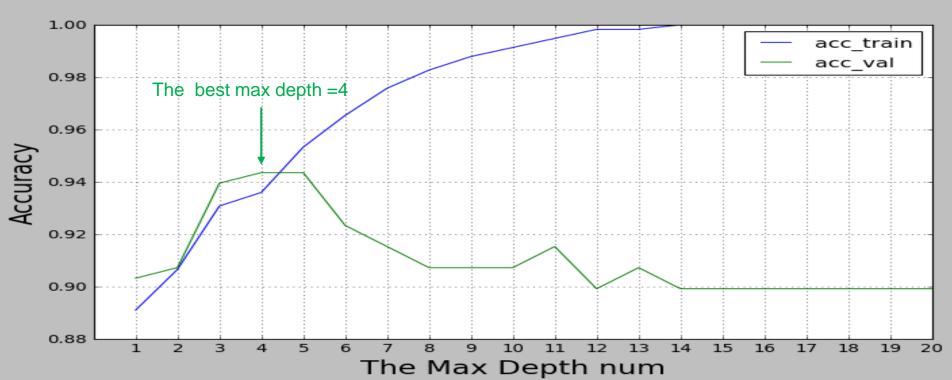
# Decision Tree Algorithm

**DT** Algorithm.

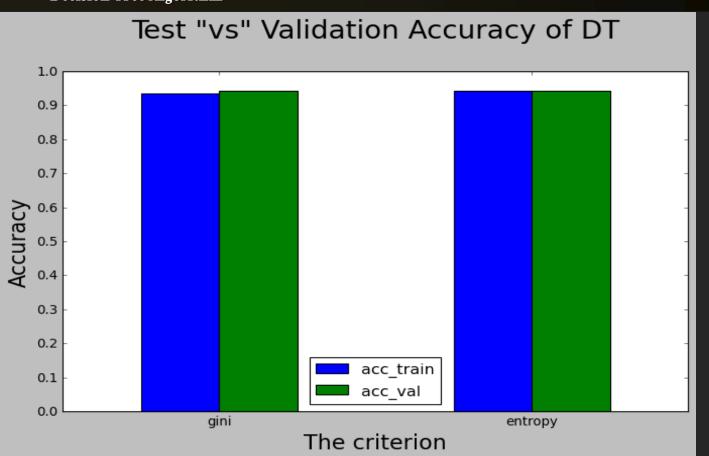


**Decision Tree Algorithm** 

#### Train "vs" Validation Accuracy of "Max Depth"



**Decision Tree Algorithm** 



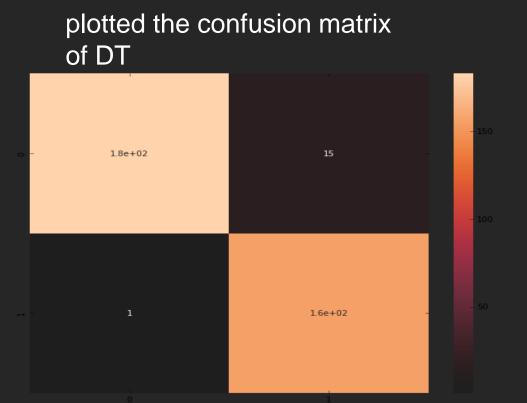


**Decision Tree Algorithm** 

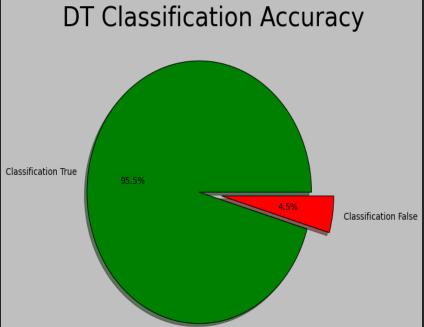
• We applied the DecisionTreeClassifier with max depth=4, criterion="entropy"

```
best_dt_model=DecisionTreeClassifier(max_depth=4,criterion='entropy',random_state=0)
best_dt_model.fit(X_train,y_train)
y_pred_test=best_dt_model.predict(X_test)
model_dt_final=accuracy_score(y_test,y_pred_test)
print(round(model_dt_final,3)*100,"%")
```

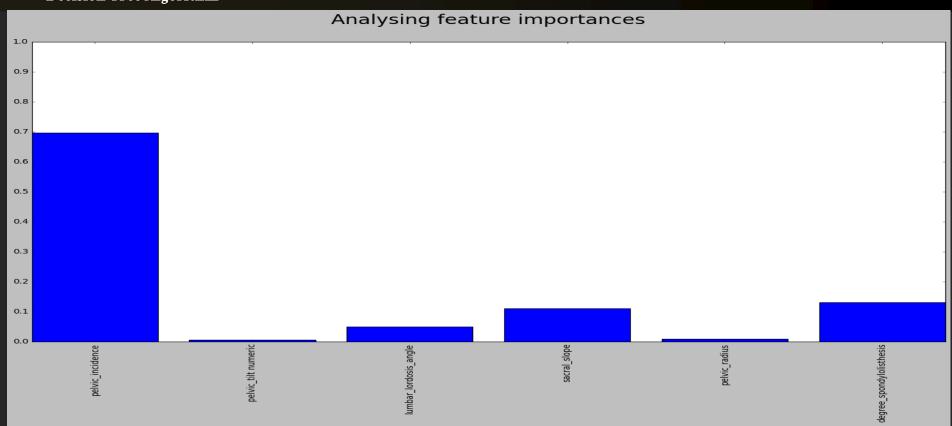
**Decision Tree Algorithm** 



DT Accuracy = 95.5%

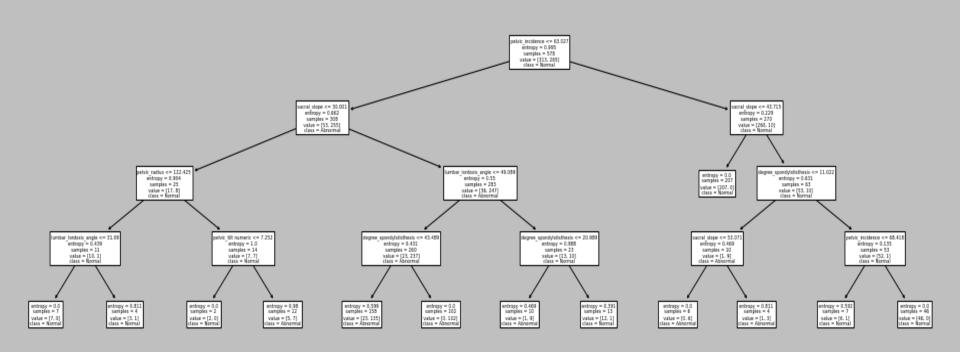


**Decision Tree Algorithm** 



**Decision Tree Algorithm** 

# Visualizing the model

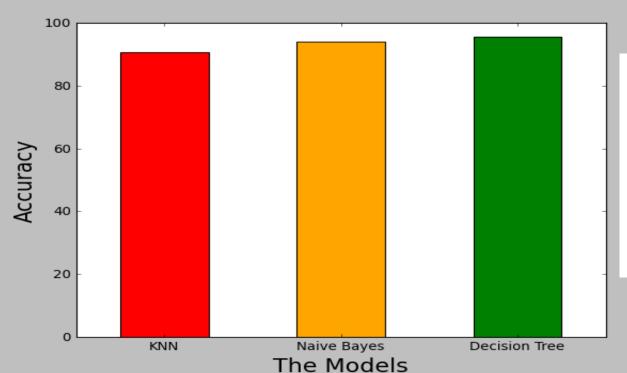


# Conclusion.

#### Conclusion.

Compare The Accuracy Of Each Model

#### Final accurse for each model to make the decision



	models	final accurase
0	KNN	90.7
1	Naive Bayes	94.1
2	Decision Tree	95.5

#### Conclusion.

The Decision of solving problem.

• When a new orthopedic patient comes to the hospital, we will be able to largely classify if he is normal or abnormal by adding some new biomechanical features to the model.

• We can conclude that "Decision Tree Algorithm" works well for data because it has a high accuracy of 95.5%.



Any Questions?