Random Forest

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Outline

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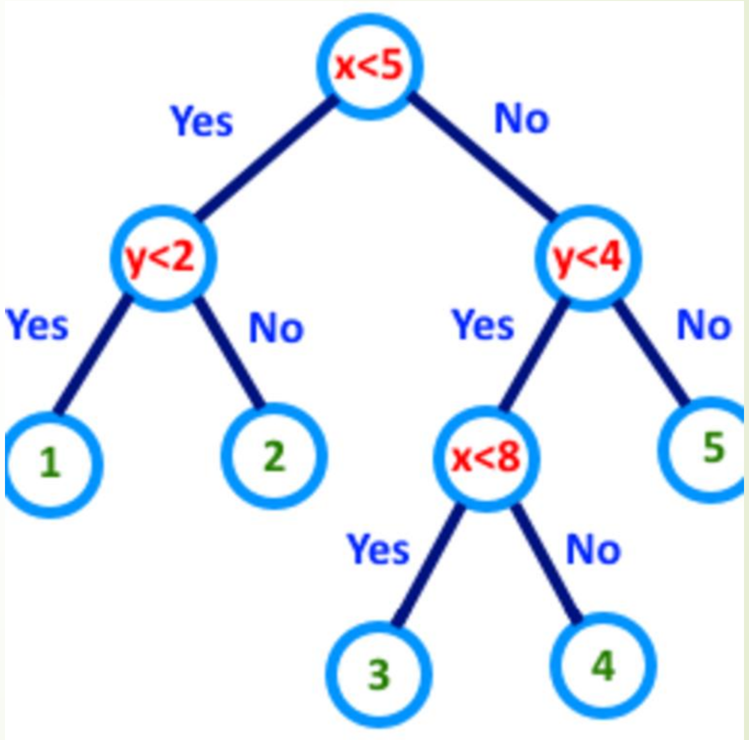
Random Forest

Random Forest is a machine learning algorithm that is used to solve regression and classification problems

The algorithm creates multiple decision trees during training and makes a prediction for those decision trees



Data

We used the Pima Indians Diabetes Database, available on Kaggle.

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

Data Processing

Changing all 0 values in the dataset to NaN excluding pregnancies and the outcome

```
for i in df.columns:
    df[i] = pd.to_numeric(df[i], downcast='integer', errors='coerce')
df.Glucose = df.Glucose.replace(0, np.nan)
df.BloodPressure = df.BloodPressure.replace(0, np.nan)
df.SkinThickness = df.SkinThickness.replace(0, np.nan)
df.Insulin = df.Insulin.replace(0, np.nan)
df.BMI = df.BMI.replace(0, np.nan)
df.DiabetesPedigreeFunction = df.DiabetesPedigreeFunction.replace(0, np.nan)
df.Age = df.Age.replace(0, np.nan)
```

Changing all NaN values to the mean of the column

```
mode_impute = SimpleImputer(missing_values = np.nan, strategy='mean')
mode_impute.fit(df['Insulin'].values.reshape(-1,1))
df[['Insulin']] = mode_impute.transform(df[['Insulin']])

mode_impute.fit(df['Glucose'].values.reshape(-1,1))
df[['Glucose']] = mode_impute.transform(df[['Glucose']])

mode_impute.fit(df['BloodPressure'].values.reshape(-1,1))
df[['BloodPressure']] = mode_impute.transform(df[['BloodPressure']])

mode_impute.fit(df['SkinThickness'].values.reshape(-1,1))
df[['SkinThickness']] = mode_impute.transform(df[['SkinThickness']])

mode_impute.fit(df['BMI'].values.reshape(-1,1))
df[['BMI']] = mode_impute.transform(df[['BMI']])
```

Updated Data Frame

Note: 0 entries are gone and replaced with the mean.

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148.0	72.0	35.00000	155.548223	33.6	0.627	50	1
1	1	85.0	66.0	29.00000	155.548223	26.6	0.351	31	0
2	8	183.0	64.0	29.15342	155.548223	23.3	0.672	32	1
3	1	89.0	66.0	23.00000	94.000000	28.1	0.167	21	0
4	0	137.0	40.0	35.00000	168.000000	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101.0	76.0	48.00000	180.000000	32.9	0.171	63	0
764	2	122.0	70.0	27.00000	155.548223	36.8	0.340	27	0
765	5	121.0	72.0	23.00000	112.000000	26.2	0.245	30	0
766	1	126.0	60.0	29.15342	155.548223	30.1	0.349	47	1
767	1	93.0	70.0	31.00000	155.548223	30.4	0.315	23	0

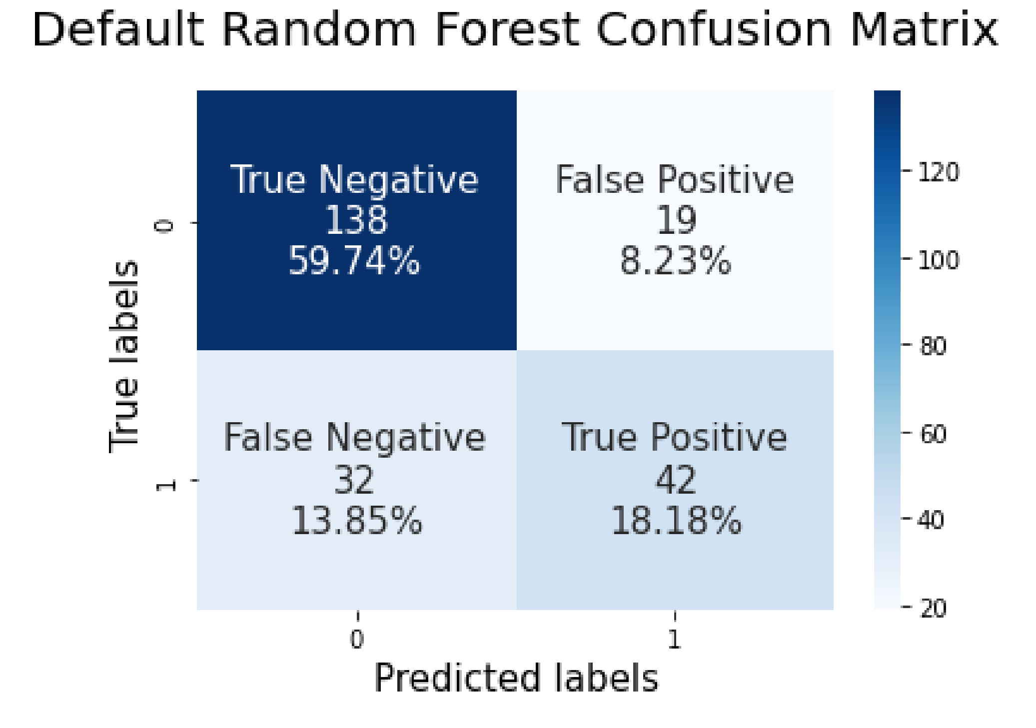
Random Forest (Default Parameters)

The mean accuracy is about 77.92%

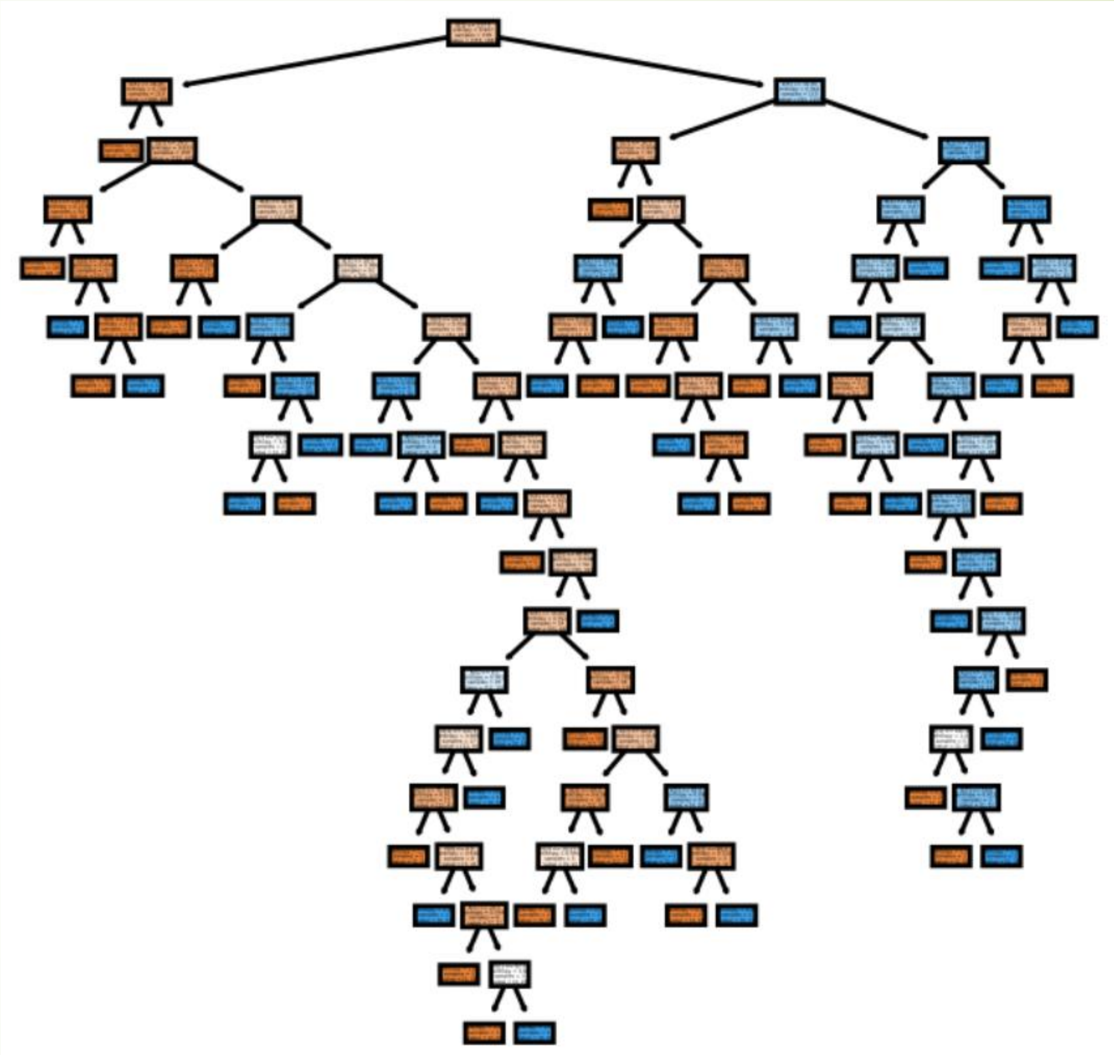
Default Parameters:

- N_estimators =100
- Max_depth = None
- ETC

```
#First Random Forest with default parameters
clf = RandomForestClassifier(criterion='entropy',random_state=0)
```



- Lots of Nodes
- Complex

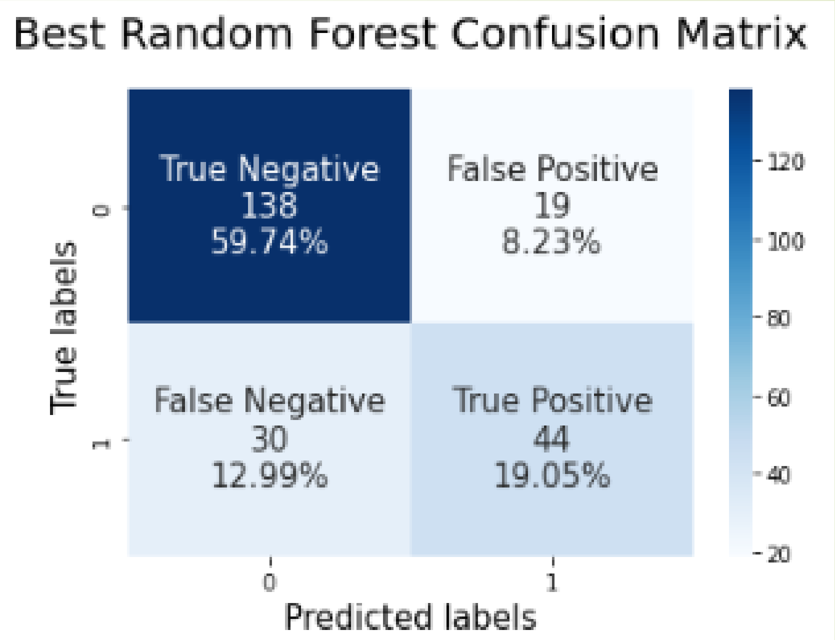


Random Forest (Adjusted Parameters)

Adjusting the hyper parameters allowed for greater accuracy. With an accuracy of **78.79%** this model proved to be the best outcome.

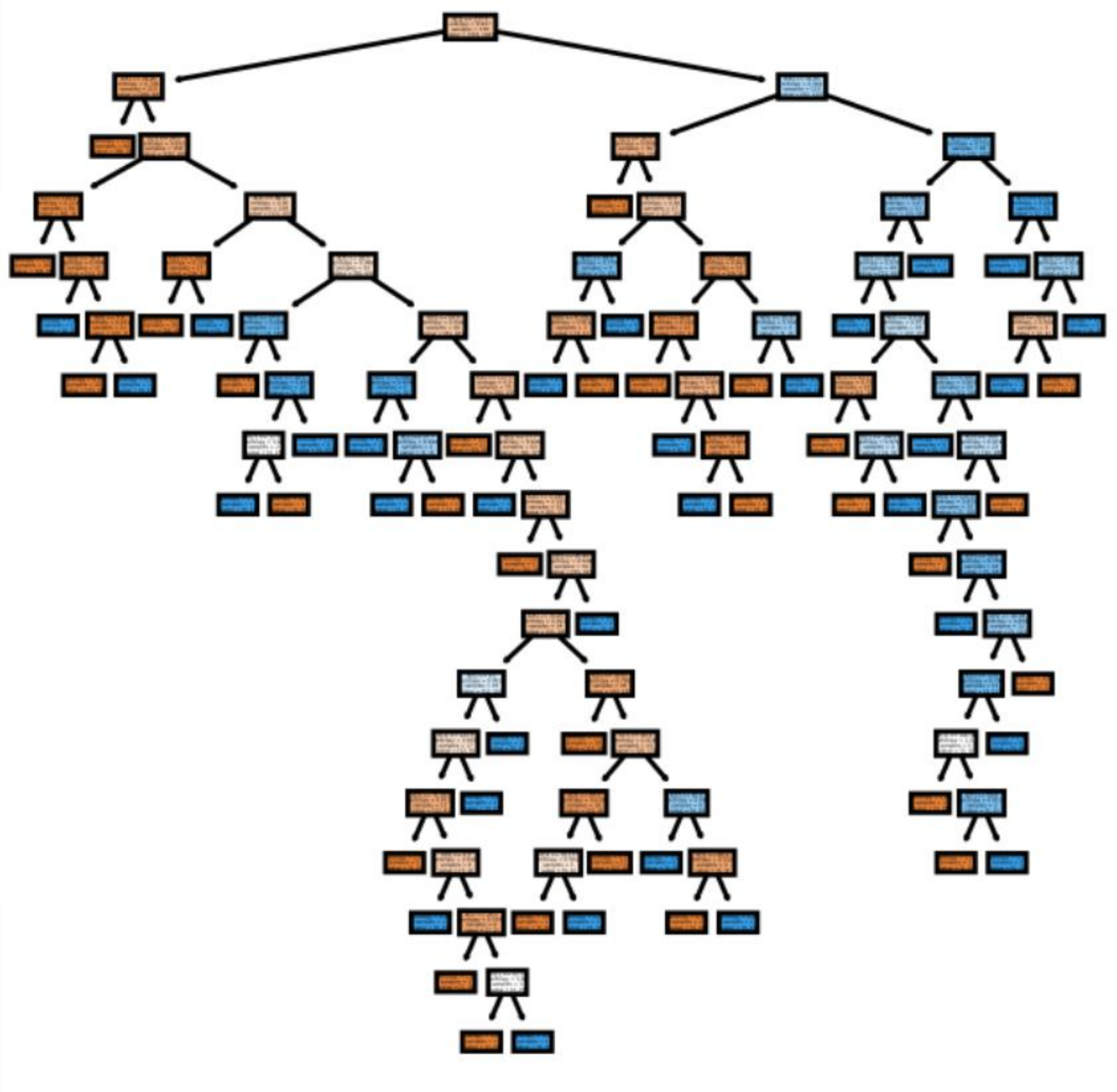
Attempted Parameters include:

- Booststrap
- max_depth
- min_samples_leaf
- max_leaf_nodes
- n_estimators



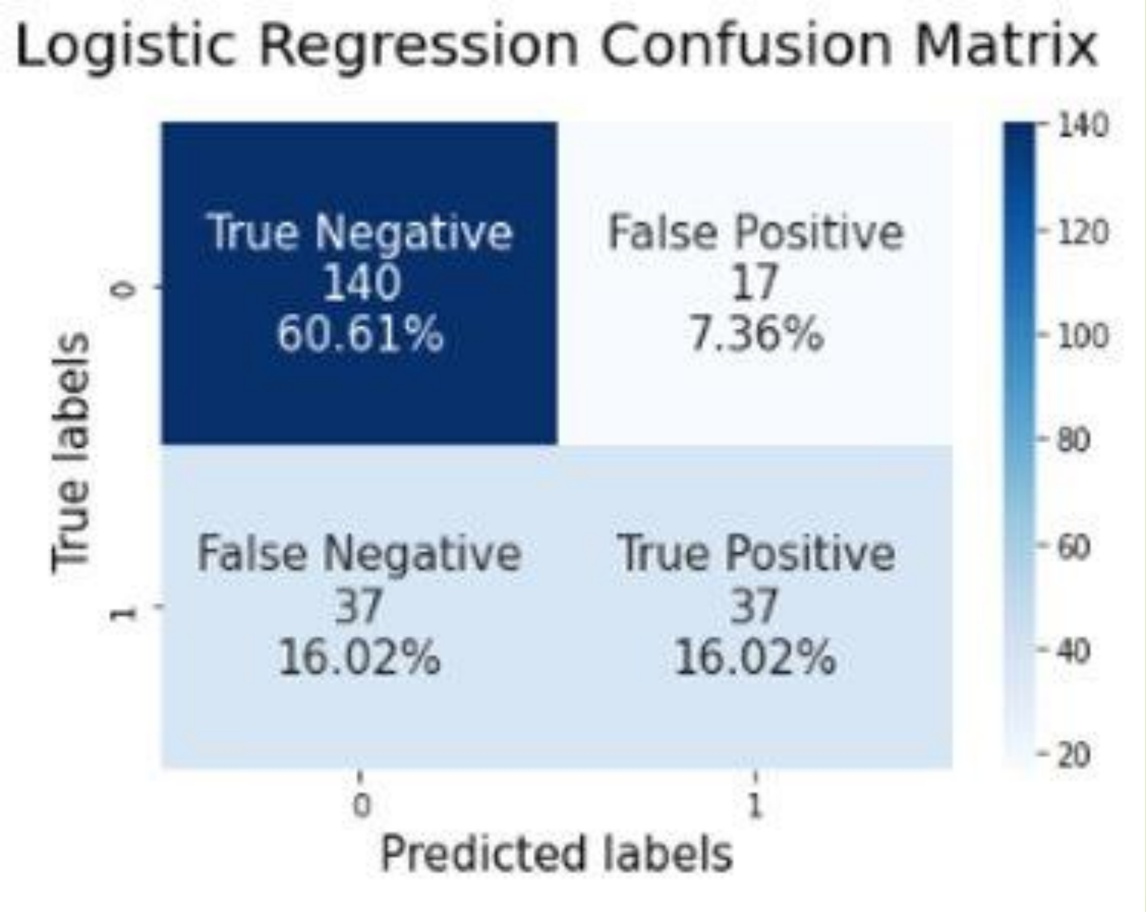

```
#Testing diff Param
#Best Model for random forest
clf2 = RandomForestClassifier(criterion='entropy',random_state=0,max_features=8)
```

- Pregnancies attribute is at the top
- Complex



Logistic Regression

This CM represents the results of an optimized Logistic Regression model run on the same dataset, prepared the same way. It achieved an average score of 76.62%, erring on the side of positive results.




```
#Logistic Regression
from sklearn.linear_model import LogisticRegressionCV
clf3 = LogisticRegressionCV(cv=5, random_state=0,max_iter=500,Cs=8).fit(X_train,y_train)
```

```
#Logistic Regression Coefficients
clf3.coef_
```

```
array([[ 0.09310639,  0.03785255, -0.01796133, -0.00796755, -0.00068314,
         0.10657938,  0.47945333,  0.02442719]])
```

```
clf3.intercept_
```

```
array([-8.68191115])
```

Comparison

- Overall adjusting the hyper-parameter max_features in the Random Forest model increased the accuracy by 0.87%, which isn’t much but nonetheless an improvement.
- When comparing the Adjusted Random Forest to the logistic regression we can see that the Random Forest has a higher accuracy by 2.17%
- Logistic Regression is less complex than Random Forest