Data Mining Project

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You might already be on my website but if you're not feel free to come by and test the outputs of this models:

https://ed.bearkillerpt.xyz/

The paper built a website just with flask. I'm personally very fond of js and particularly ReactJs and so I used Flask to build an api that I can query to get the results! If you wish to use it an example of a request, as available on the dev console of your browser:

https://edapi.bearkillerpt.xyz/?age=20&gender=0&hypertension=0&heart_disease=0&ever_married=0&work_type=0&Residence_
For more information on how the parameters were encoded check the web-api.py script on my github page:

https://github.com/bearkillerPT/DataMining/blob/main/WebApp/web-api.py

The paper selected is named:

Analyzing the Performance of Stroke Prediction using ML Classification Algorithms [1]

In [ ]:
```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import sklearn as sk
import imblearn
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB

from sklearn.model_selection import train_test_split
import sklearn.metrics as metrics
print("Using pandas %s version" % pd.__version__)
print("Using numpy %s version" % np.__version__)
print("Using sklearn %s version" % sk.__version__)
print("Using imblearn %s version" % imblearn.__version__)
```

```
Using pandas 1.3.4 version
Using numpy 1.20.3 version
Using sklearn 1.0.2 version
Using imblearn 0.9.0 version
```

Index

First the data must be PreProcessed! We drop the id column as it doesn't make any diference for the models performance. Then we must substitute NaN (null) entries with the class means in this case, as pointed by the paper, exclusively the column bmi. Finally we must encode the 5 non-numerical variables to numeric ones!

In [ ]:
```
dataset = pd.read_csv('./dataset/healthcare-dataset-stroke-data.csv')
df_dataset = pd.DataFrame(data=dataset)

#Dropping 'id' column
df_dataset.drop('id', axis=1, inplace=True)

#Substituting NaN (null) entries with the bmi means
df_dataset['bmi'].fillna(df_dataset['bmi'].mean(), inplace=True)
categoric_vars = ["gender","ever_married","work_type","Residence_type","smoking_stat
#Encoding of non-numerical variables!
for categoric_var in categoric_vars:
    df_dataset[categoric_var].replace({label: int(idx) for idx, label in enumerate(n

print(df_dataset.head())
```

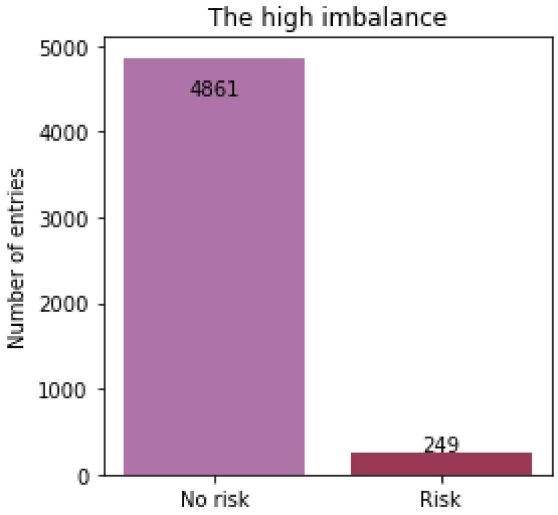
```
   gender   age  hypertension  heart_disease  ever_married  work_type  \
0       1  67.0             0              1             1          2
1       0  61.0             0              0             1          3
2       1  80.0             0              1             1          2
3       0  49.0             0              0             1          2
4       0  79.0             1              0             1          3

   Residence_type  avg_glucose_level        bmi  smoking_status  stroke
0               1             228.69  36.600000               1       1
1               0             202.21  28.893237               2       1
2               0             105.92  32.500000               2       1
3               1             171.23  34.400000               3       1
4               0             174.12  24.000000               2       1
```

The big imbalance

As noted by the authors the data is highly imbalanced! As shown in the plot bellow there are way more entries for no risk of stroke then for having risk of one. Of the 5110 entries only 249 correspond to patients with risk of stroke! The paper suggest to under-sample the 'no rist' to match the amount of 'risk' entries. In this notebook we will also expolore over-sampling the 'risk'

entries to match the 'no risk' ones! This might be advantageous as more information is passed about the data set while not having a huge bias twoards 'no risk'.

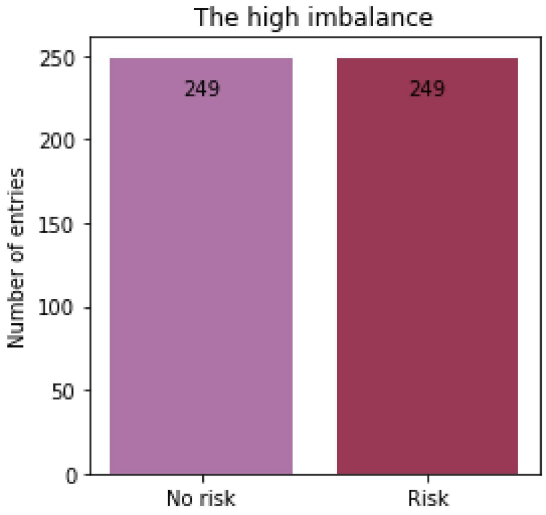
In [ ]:
```
def plot_imbalance(dataset):
        no_risk_count = dataset["stroke"].loc[dataset["stroke"] == 0].count()
        risk_count = dataset["stroke"].loc[dataset["stroke"] == 1].count()
        bar_data = [no_risk_count, risk_count]
        plt.figure(figsize=(4,4))
        bar_plot = plt.bar(["No risk", "Risk"], bar_data, color=['#AE76A6', '#993955
        for idx,rect in enumerate(bar_plot):
                height = rect.get_height()
                plt.text(rect.get_x() + rect.get_width()/2., 0.9*height,
                        bar_data[idx],
                        ha='center', va='bottom', rotation=0)
        plt.title("The high imbalance")
        plt.ylabel("Number of entries")
        plt.show()
plot_imbalance(df_dataset)
```



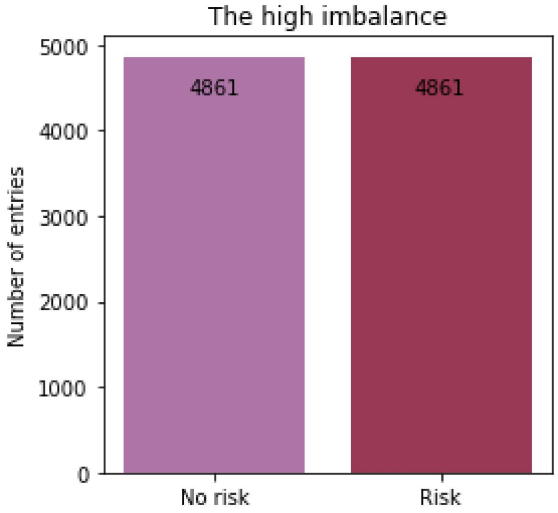
To handle this imbalance and as not to produce models with very high accuracy but with very poor results in other very important metrics that will be used to compare the multiple models addressed! The technique used in the paper references '7 Techniques to Handle Imbalanced Data – Kdnuggets' and the majority class is under-sampled to match the minority class. Over-sampling will also be performed to compare both!

In [ ]:
```
#Over-sampling
oversample = SMOTE()
over_x, over_y = oversample.fit_resample(df_dataset.drop(
    'stroke', axis=1), df_dataset['stroke'].astype('int') )
oversampled_data = over_x.join(over_y)

#Under-sampling
df_dataset.loc[df_dataset["stroke"] == 0] = df_dataset.loc[df_dataset["stroke"] == 0
df_dataset.dropna(inplace=True)
df_dataset.reset_index(drop=True, inplace=True)


print("After Under-sample:")
plot_imbalance(df_dataset)
print("After Over-sample:")
plot_imbalance(oversampled_data)
```

```
After Under-sample:
```




```
After Over-sample:
```



Since our prediction target is boolean it makes a lot of sense to try first the logistic regression! The results for the multiple metrics throughout this notebook will change per each run since the train and test sets have different samples!

Machine Learning Algorithm Models

Before modeling we must separate our data intro training and testing data sets! Furthermore some useful functions that will be reused by every model are defined here. Moreover it's important to note that from now we will build every model for both uner and over-sampled data!

In [ ]:

```
x_train, x_test, y_train, y_test = train_test_split(df_dataset.drop(
    'stroke', axis=1), df_dataset['stroke'].astype('int'), test_size=0.2)
over_x_train, over_x_test, over_y_train, over_y_test = train_test_split(over_x, over
stats = {}
# useful functions for the model stats!


def print_stats(cls_name, y_test, prediction):
    print(cls_name + " metrics:")
    sample_type = cls_name.split(' ')[0]
    cls_name = ' '.join(cls_name.split(' ')[1:])
    print(sample_type)
    print(cls_name)
```

```
    if cls_name not in stats.keys():
        stats[cls_name] = {}
    stats[cls_name][sample_type] = {}
    stats[cls_name][sample_type] = {
        "accuracy":  metrics.accuracy_score(y_test, prediction),
        "precision":  metrics.average_precision_score(y_test, prediction),
        "recall":  metrics.recall_score(y_test, prediction),
        "f1_score": metrics.f1_score(y_test, prediction)
    }
    print("Accuracy: " + str(stats[cls_name][sample_type]["accuracy"]))
    print("Precision: " + str(stats[cls_name][sample_type]["precision"]))
    print("Recall: " + str(stats[cls_name][sample_type]["recall"]))
    print("F1 score: " + str(stats[cls_name][sample_type]["f1_score"]))


def show_roc_curve(cls, x_test, y_test):
    probs = cls.predict_proba(x_test)
    preds = probs[:, 1]
    fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
    roc_auc = metrics.auc(fpr, tpr)
    print("Receiver operating characteristic (ROC) curve:")
    metrics.RocCurveDisplay(fpr=fpr, tpr=tpr, roc_auc=roc_auc).plot()
```

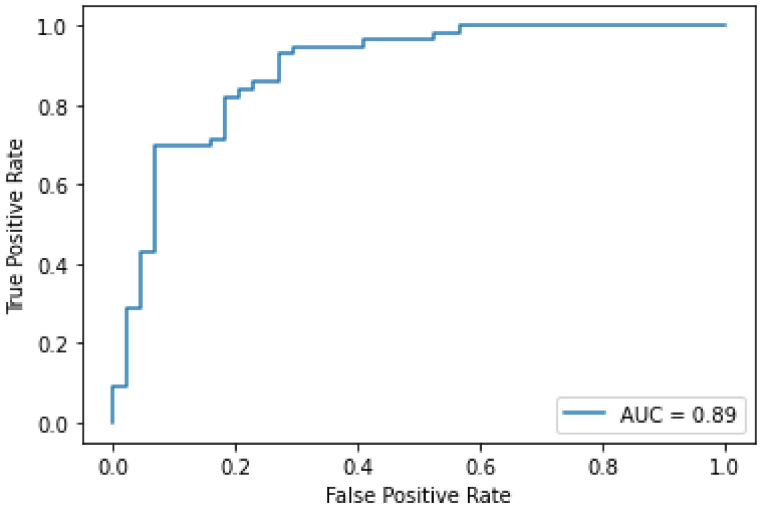
Logistic Regression

Under-sampling

In [ ]:

```
logistic_classifier = LogisticRegression(max_iter=1000)
under_log_model = logistic_classifier.fit(x_train, y_train)
under_prediction = logistic_classifier.predict(x_test)
print_stats("Under-sampled Logistic Regression", y_test, under_prediction)
show_roc_curve(under_log_model, x_test, y_test)
```

```
Under-sampled Logistic Regression metrics:
Under-sampled
Logistic Regression
Accuracy: 0.78
Precision: 0.77
Recall: 0.75
F1 score: 0.7924528301886793
Receiver operating characteristic (ROC) curve:
```



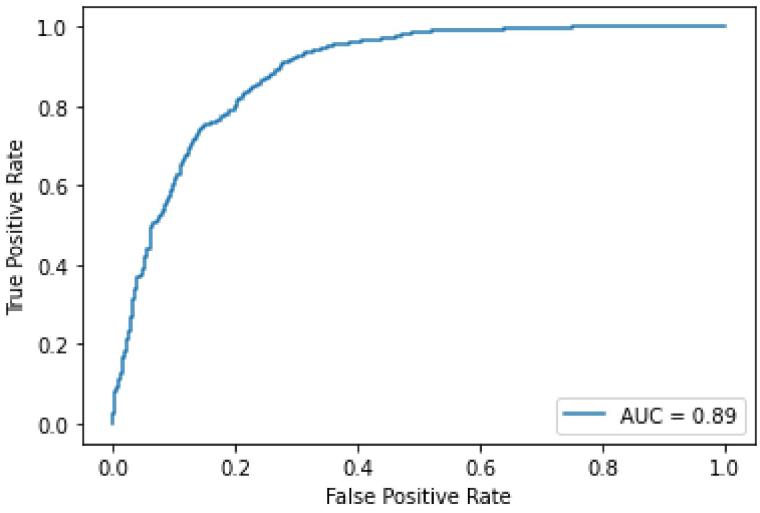
Over-sampling

In [ ]:

```
over_log_model = logistic_classifier.fit(over_x_train, over_y_train)
```

```
over_prediction = logistic_classifier.predict(over_x_test)
print_stats("Over-sampled Logistic Regression", over_y_test, over_prediction)
show_roc_curve(over_log_model, over_x_test, over_y_test)
```

```
Over-sampled Logistic Regression metrics:
Over-sampled
Logistic Regression
Accuracy: 0.8051413881748072
Precision: 0.7425139429046461
Recall: 0.819773429454171
F1 score: 0.8077118214104516
Receiver operating characteristic (ROC) curve:
```



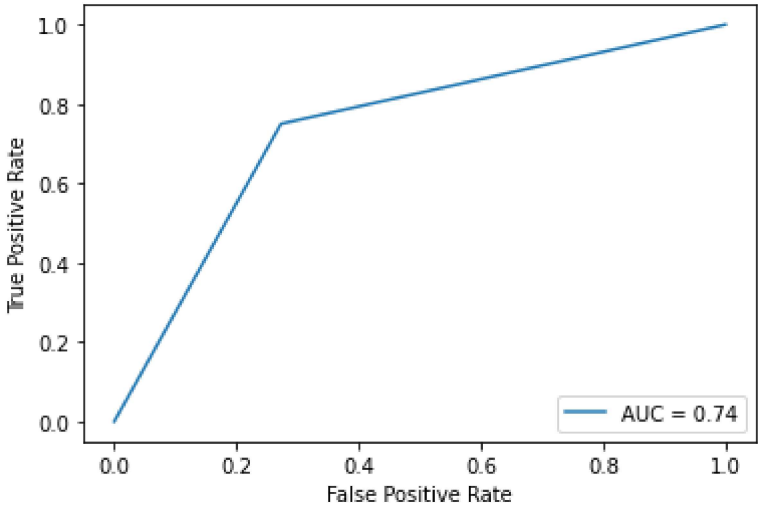
Decision Tree Classification

Under-sampling

In [ ]:

```
decision_tree_cls = tree.DecisionTreeClassifier()
under_decision_tree_model = decision_tree_cls.fit(x_train, y_train)
prediction = under_decision_tree_model.predict(x_test)
print_stats("Under-sampled Decision Tree", y_test, prediction)
show_roc_curve(under_decision_tree_model, x_test, y_test)
```

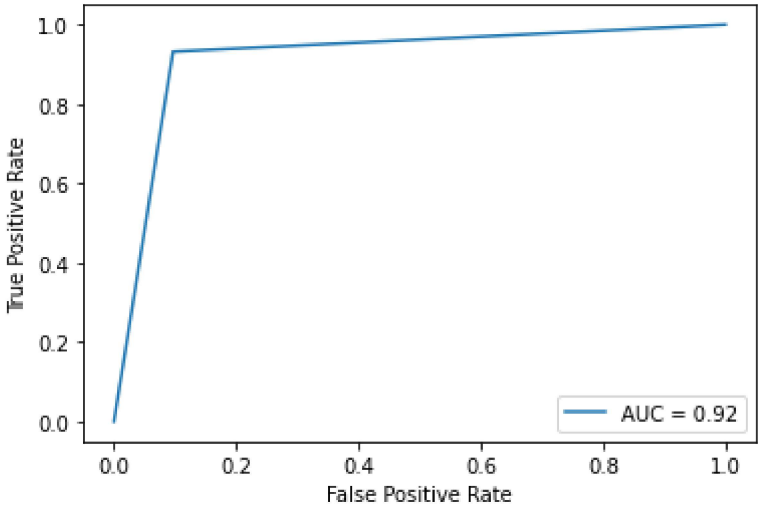
```
Under-sampled Decision Tree metrics:
Under-sampled
Decision Tree
Accuracy: 0.74
Precision: 0.7233333333333334
Recall: 0.75
F1 score: 0.7636363636363638
Receiver operating characteristic (ROC) curve:
```



Over-sampling

In [ ]:
```
over_decision_tree_model = decision_tree_cls.fit(over_x_train, over_y_train)
prediction = under_decision_tree_model.predict(over_x_test)
print_stats("Over-sampled Decision Tree", over_y_test, prediction)
show_roc_curve(over_decision_tree_model, over_x_test, over_y_test)
```

```
Over-sampled Decision Tree metrics:
Over-sampled
Decision Tree
Accuracy: 0.9177377892030848
Precision: 0.8782635891883772
Recall: 0.9320288362512873
F1 score: 0.9187817258883249
Receiver operating characteristic (ROC) curve:
```



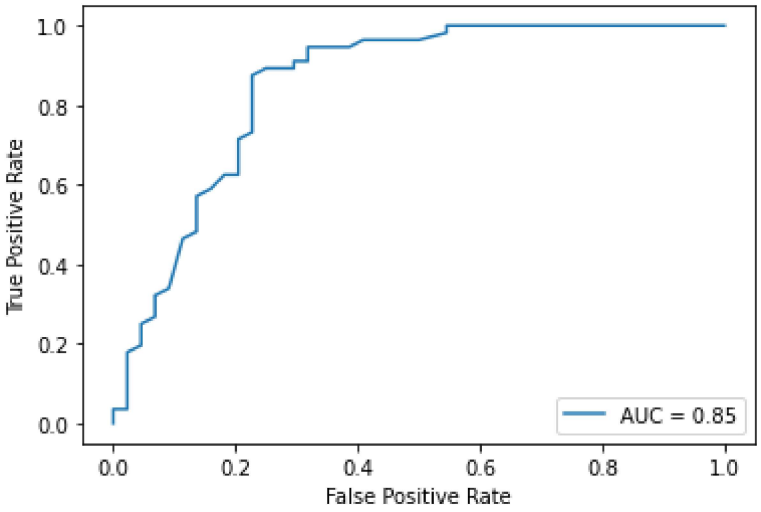
Random Forest Classification

Under-sampling

In [ ]:
```
random_forest_cls = RandomForestClassifier()
under_random_forest_model = random_forest_cls.fit(x_train, y_train)
prediction = under_random_forest_model.predict(x_test)
print_stats("Under-sampled Random Forest", y_test, prediction)
show_roc_curve(under_random_forest_model, x_test, y_test)
```

```
Under-sampled Random Forest metrics:
```

```
Under-sampled
Random Forest
Accuracy: 0.78
Precision: 0.7602116402116401
Recall: 0.7857142857142857
F1 score: 0.7999999999999999
Receiver operating characteristic (ROC) curve:
```

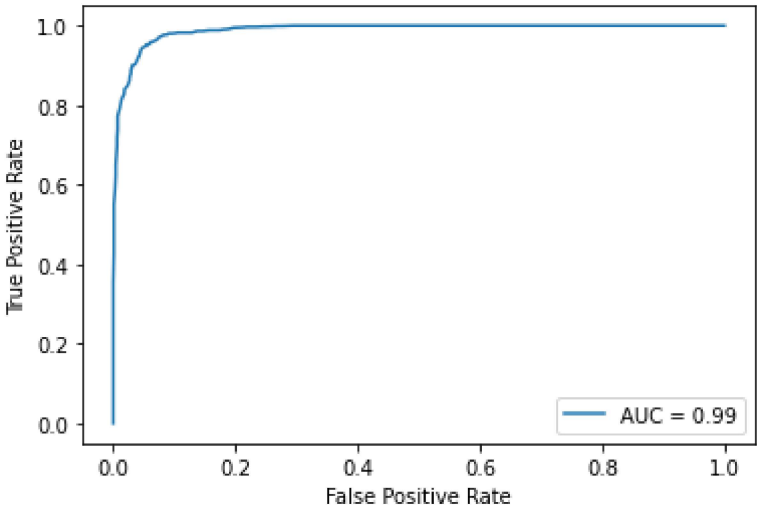


Over-sampling

In [ ]:

```
over_random_forest_model = random_forest_cls.fit(over_x_train, over_y_train)
prediction = over_random_forest_model.predict(over_x_test)
print_stats("Over-sampled Random Forest", over_y_test, prediction)
show_roc_curve(over_random_forest_model, over_x_test, over_y_test)
```

```
Over-sampled Random Forest metrics:
Over-sampled
Random Forest
Accuracy: 0.9470437017994858
Precision: 0.9155163856289102
Recall: 0.9670442842430484
F1 score: 0.9480060575466935
Receiver operating characteristic (ROC) curve:
```



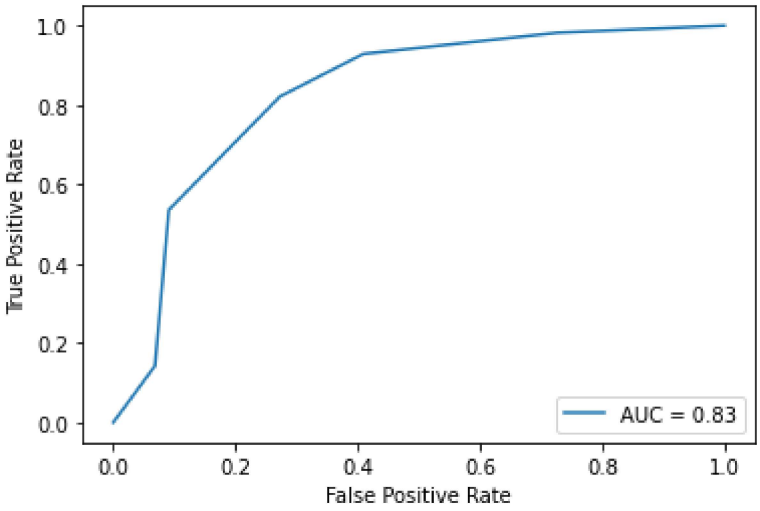
Like the Decision Tree model the Random Forest one behaves way better with over-sampling!

K-nearest neighbors

Under-sampling

In [ ]:
```
k_nearest_neighbors_cls = KNeighborsClassifier()
under_k_nearest_neighbors_model = k_nearest_neighbors_cls.fit(x_train, y_train)
prediction = under_k_nearest_neighbors_model.predict(x_test)
print_stats("Under-sampled K-nearest neighbors", y_test, prediction)
show_roc_curve(under_k_nearest_neighbors_model, x_test, y_test)
```

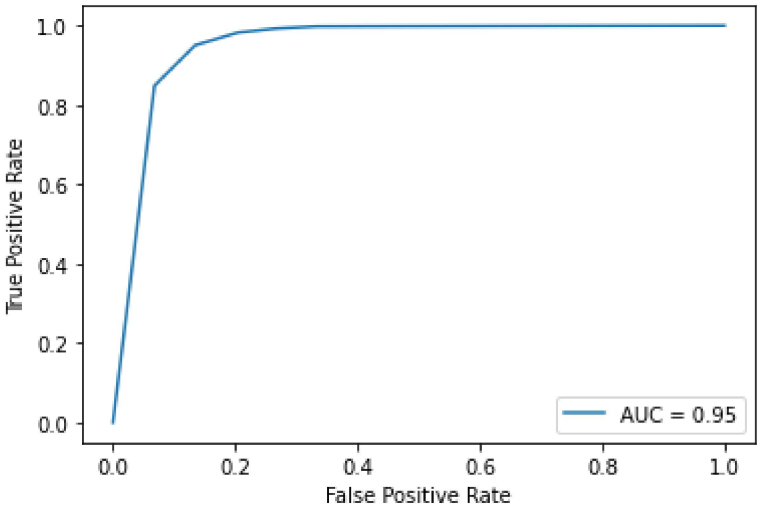
```
Under-sampled K-nearest neighbors metrics:
Under-sampled
K-nearest neighbors
Accuracy: 0.78
Precision: 0.7514778325123153
Recall: 0.8214285714285714
F1 score: 0.8070175438596492
Receiver operating characteristic (ROC) curve:
```



Over-Sampling

In [ ]:
```
over_k_nearest_neighbors_model = k_nearest_neighbors_cls.fit(over_x_train, over_y_tr
prediction = over_k_nearest_neighbors_model.predict(over_x_test)
print_stats("Over-sampled K-nearest neighbors", over_y_test, prediction)
show_roc_curve(over_k_nearest_neighbors_model, over_x_test, over_y_test)
```

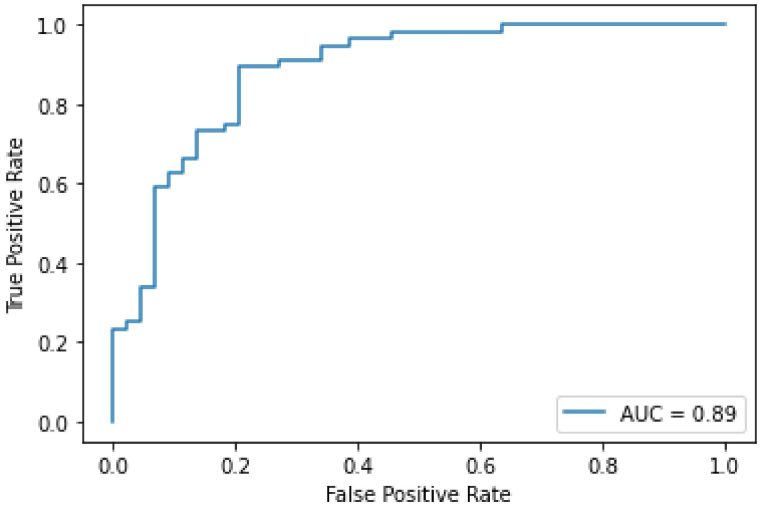
```
Over-sampled K-nearest neighbors metrics:
Over-sampled
K-nearest neighbors
Accuracy: 0.8889460154241645
Precision: 0.8216611155848826
Recall: 0.9824922760041195
F1 score: 0.8983050847457628
Receiver operating characteristic (ROC) curve:
```



Support Vector Machine

In [ ]:
```
svm_cls = clf = SVC(kernel='rbf', probability=True)
under_svm_model = svm_cls.fit(x_train, y_train)
prediction = under_svm_model.predict(x_test)
print_stats("Under-sampled SVM", y_test, prediction)
show_roc_curve(under_svm_model, x_test, y_test)
```

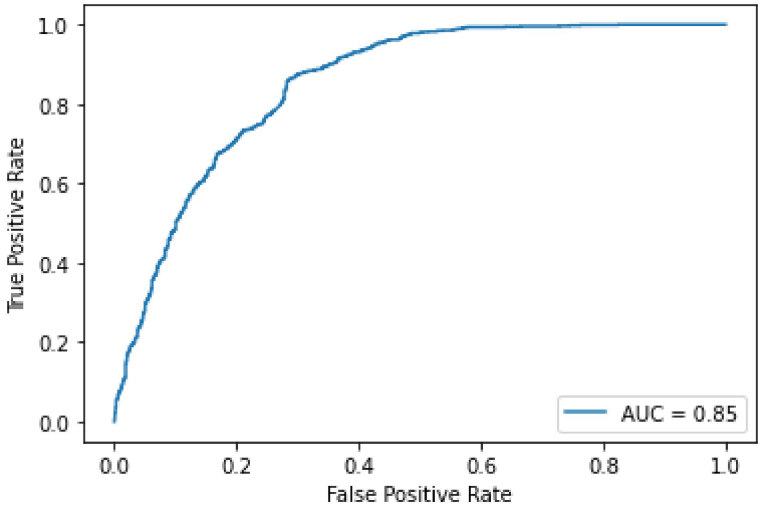
```
Under-sampled SVM metrics:
Under-sampled
SVM
Accuracy: 0.8
Precision: 0.7796428571428572
Recall: 0.8035714285714286
F1 score: 0.8181818181818182
Receiver operating characteristic (ROC) curve:
```



Over-sampling

In [ ]:
```
over_svm_model = svm_cls.fit(over_x_train, over_y_train)
prediction = over_svm_model.predict(over_x_test)
print_stats("Over-sampled SVM", over_y_test, prediction)
show_roc_curve(over_svm_model, over_x_test, over_y_test)
```

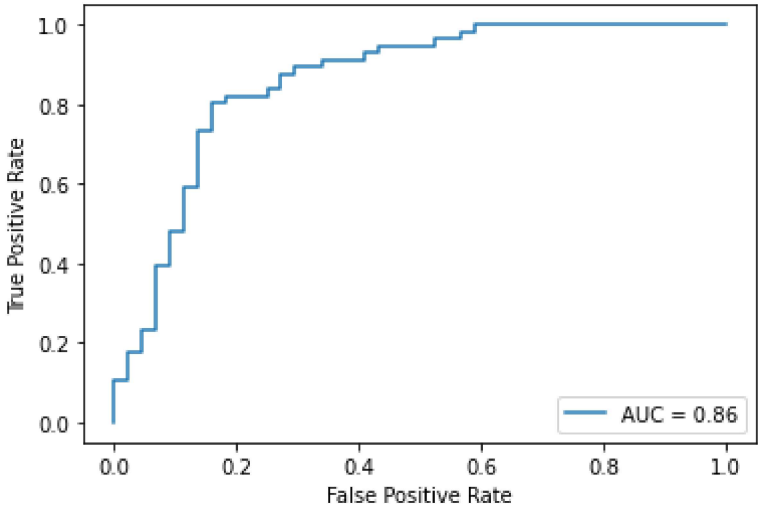
```
Over-sampled SVM metrics:
Over-sampled
SVM
Accuracy: 0.7696658097686375
Precision: 0.7006407637383814
Recall: 0.8177136972193615
F1 score: 0.7799607072691552
Receiver operating characteristic (ROC) curve:
```



Naive Bayes

In [ ]:
```
naive_bayes_cls = clf = GaussianNB()
under_naive_bayes_model = naive_bayes_cls.fit(x_train, y_train)
prediction = under_naive_bayes_model.predict(x_test)
print_stats("Under-sampled Naive Bayes", y_test, prediction)
show_roc_curve(under_naive_bayes_model, x_test, y_test)
```

```
Under-sampled Naive Bayes metrics:
Under-sampled
Naive Bayes
Accuracy: 0.76
Precision: 0.7660389610389611
Recall: 0.6785714285714286
F1 score: 0.76
Receiver operating characteristic (ROC) curve:
```

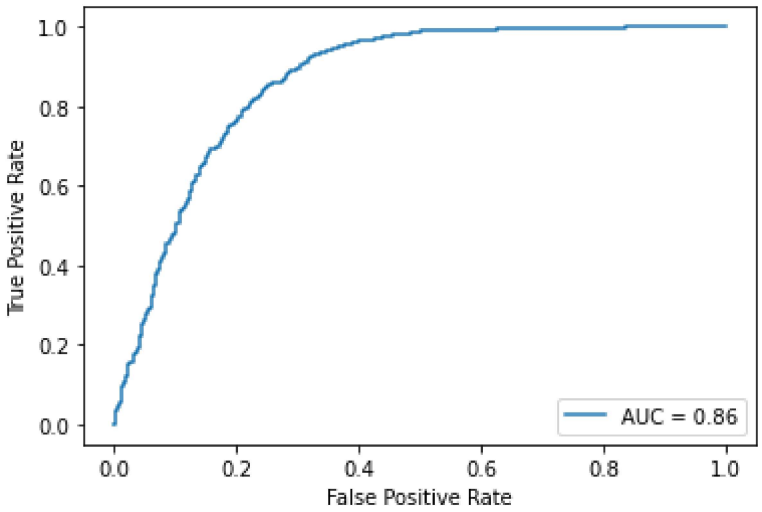


Over-sampling

In [ ]:
```
over_naive_bayes_model = naive_bayes_cls.fit(over_x_train, over_y_train)
prediction = over_naive_bayes_model.predict(over_x_test)
print_stats("Over-sampled Naive Bayes", over_y_test, prediction)
show_roc_curve(over_naive_bayes_model, over_x_test, over_y_test)
```

```
Over-sampled Naive Bayes metrics:
Over-sampled
Naive Bayes
Accuracy: 0.7958868894601543
```

```
Precision: 0.7247966706370705
Recall: 0.8619979402677652
F1 score: 0.8083051665861903
Receiver operating characteristic (ROC) curve:
```



Results

Following the tests done and with the statistcs already filled, the multiple metrics are compared in bar plots by the same order used before: accuracy, precision, recall and f1 score! For each ML Algorithm Model we will have the over-sampled statistic, in a darker color, followed by the under-sampled statistic, in a lighter color, because, most of the time, the values will be higher for the over

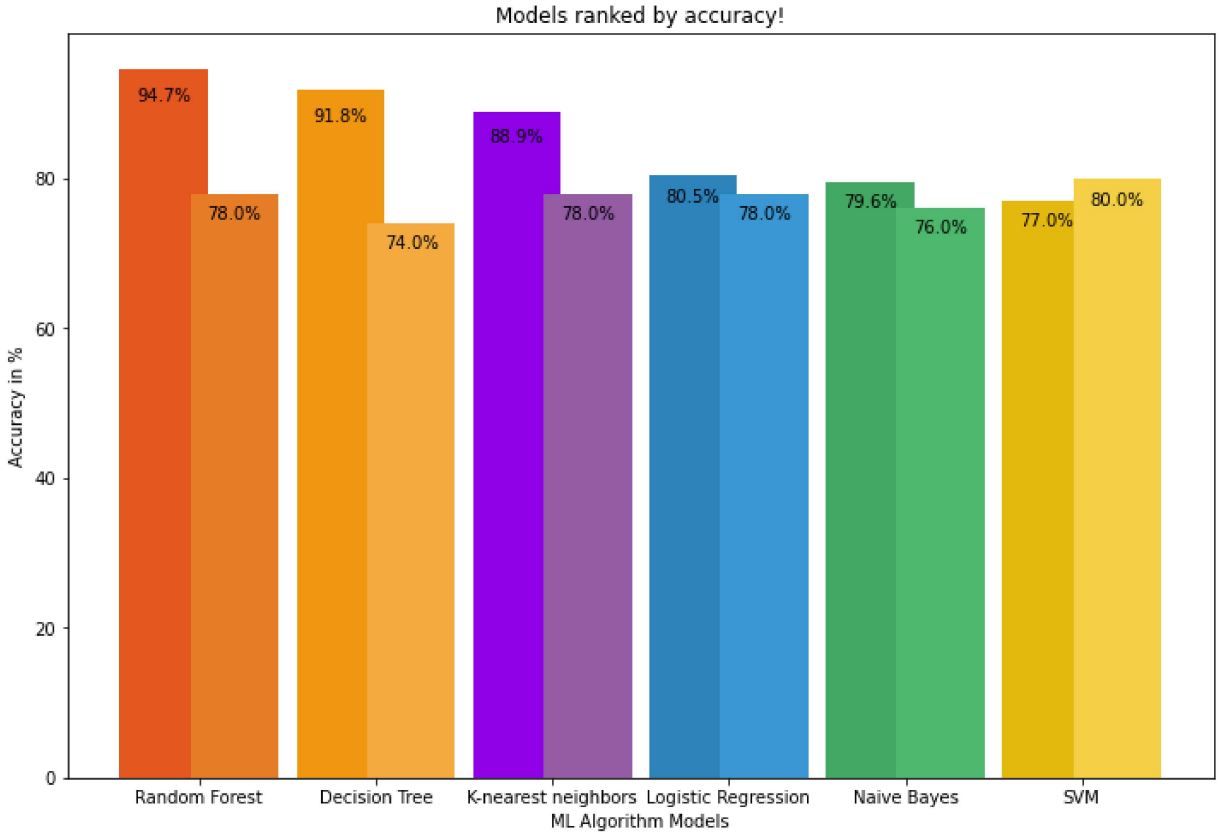
In [ ]:

```
def plot_stat(stat_name):
    colot_pallet1 = ["#e5571f", "#f0960f", "#8e00e6", "#2c83ba", "#43a863", "#e5ba10
    colot_pallet2 = ["#e57d25", "#f3ab3f", "#935ba4", "#3a96d1", "#4db86e", "#f2cf45
    stat_name_sorted_stats = dict(sorted(stats.items(),key=lambda item:item[1]["Over
    plt.figure(figsize = (12, 8))
    X_axis = np.arange(len(stat_name_sorted_stats.keys()))
    over_stat_name_sorted_values = [item["Over-sampled"][stat_name]*100 for item in
    under_stat_name_sorted_values = [item["Under-sampled"][stat_name]*100 for item i
    bar_plot1 = plt.bar(X_axis - 0.2, over_stat_name_sorted_values, color=colot_pall
    bar_plot2 = plt.bar(X_axis + 0.2, under_stat_name_sorted_values, color=colot_pal
    for idx,rect in enumerate(bar_plot1):
        height = rect.get_height()
        plt.text(rect.get_x() + rect.get_width()/2., 0.95*height,
            "{:.1f}%".format(over_stat_name_sorted_values[idx]),
            ha='center', va='bottom', rotation=0)

    for idx,rect in enumerate(bar_plot2):
        height = rect.get_height()
        plt.text(rect.get_x() + rect.get_width()/2., 0.95*height,
            "{:.1f}%".format(under_stat_name_sorted_values[idx]),
            ha='center', va='bottom', rotation=0)

    plt.xticks(X_axis, stat_name_sorted_stats)
    plt.xlabel("ML Algorithm Models")
    plt.ylabel(stat_name.title() + " in %")
    plt.title("Models ranked by " + stat_name + "!")
    plt.show()
```

This function serves to plot any stat!

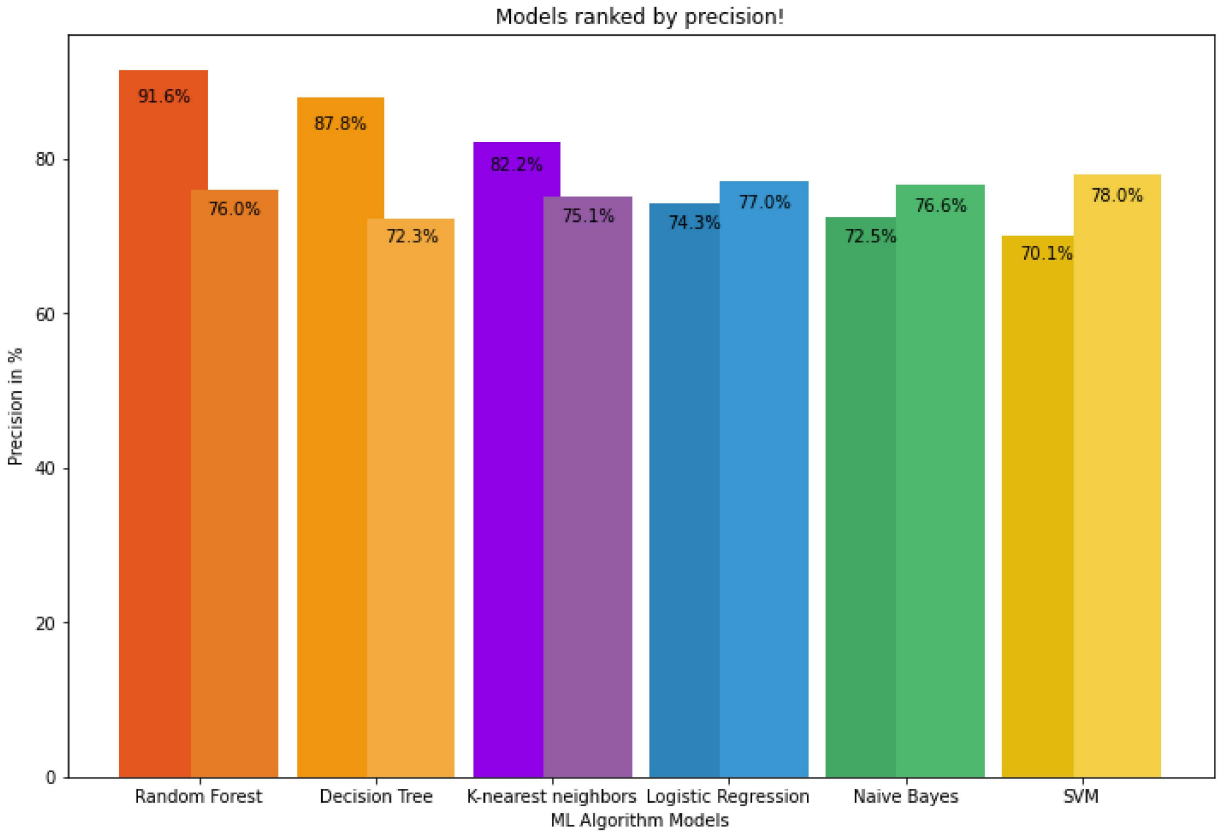
Accuracy

In [ ]:
```
plot_stat("accuracy")
```



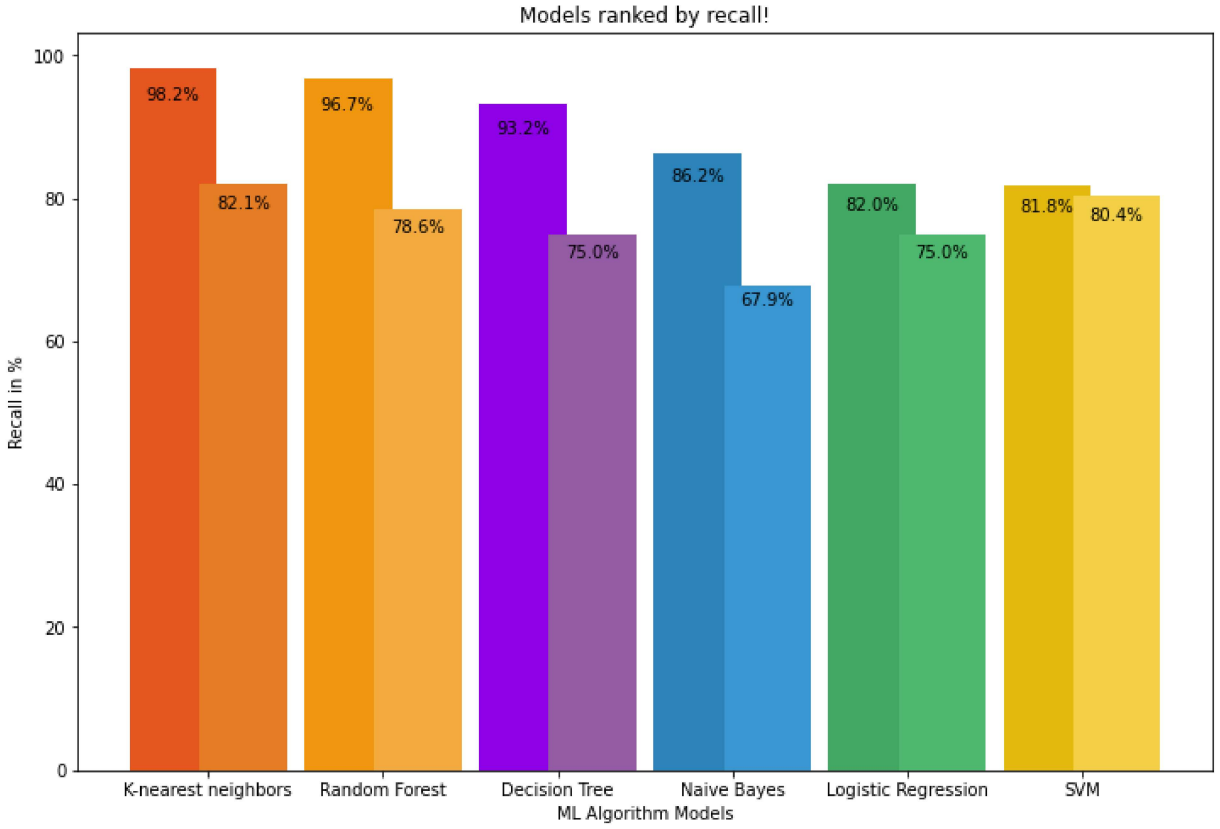
Precision

In [ ]:
```
plot_stat("precision")
```



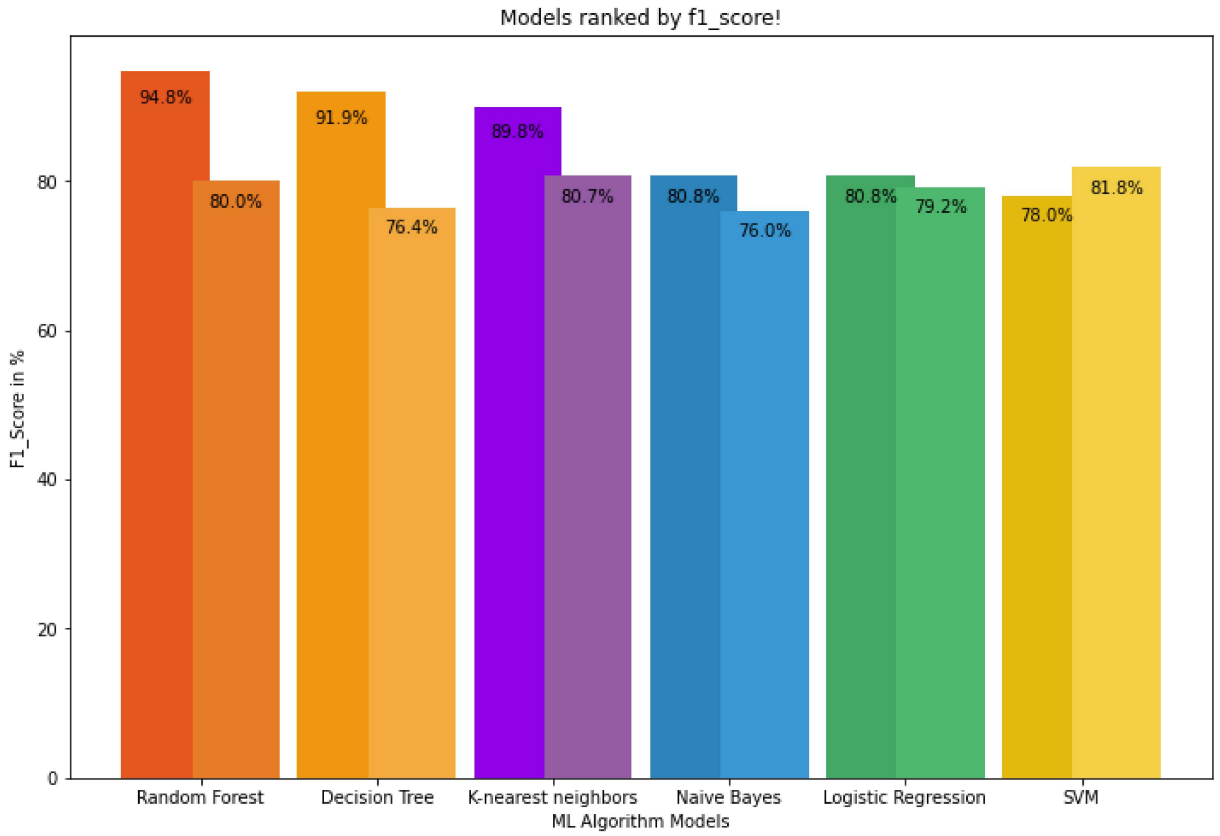
Recall

In [ ]:
```
plot_stat("recall")
```



F1 score

In [ ]:
```
plot_stat("f1_score")
```



Conclusion

The results differ very little from the ones suggested in the paper when using the under-sampling method to balance the data. Using over-sampling yields, in general, better results tho ti might come at a cost since the computational effort for the model building is increased! A ML algorithm trained on image datasets would probably lead to a better model for stroke prediction, though with some of these algorithms, on this dataset, we do get fairly good results!

References

[1] Accessed 20th of February, 2022 - https://thesai.org/Downloads/Volume12No6/Paper_62-Analyzing_the_Performance_of_Stroke_Prediction.pdf