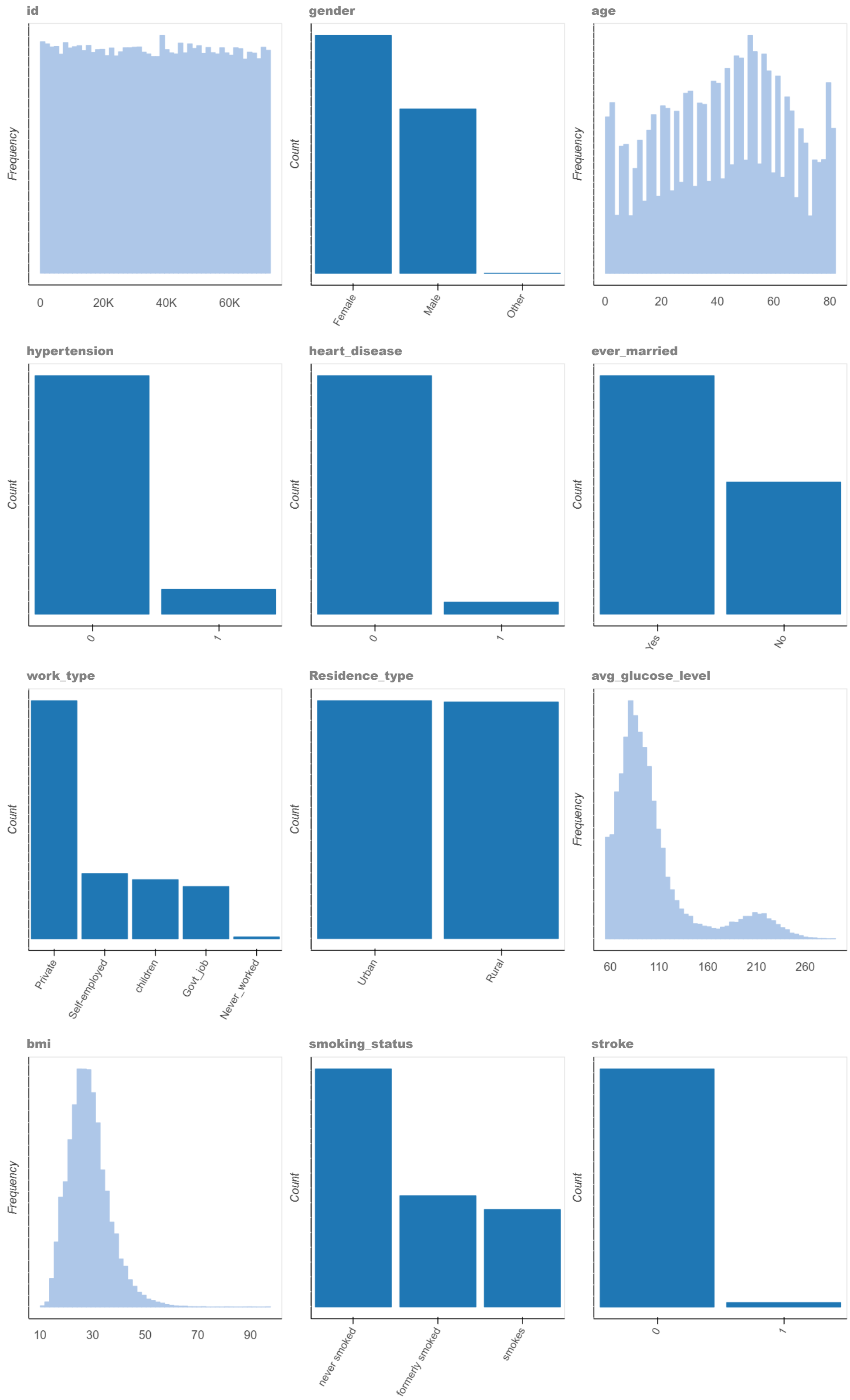
In [ ]:
```
plot(data)
```

Out[ ]:

Show Stats and Insights



Out[ ]:

DataPrep Report Overview Variables Interactions Correlations Missing Values

Overview

Dataset Statistics

Number of Variables	12
Number of Rows	43400
Missing Cells	14754
Missing Cells (%)	2.8%
Duplicate Rows	0
Duplicate Rows (%)	0.0%
Total Size in Memory	15.0 MB
Average Row Size in Memory	362.3 B
Variable Types	Numerical: 4 Categorical: 8

Dataset Insights

- `id` is uniformly distributed
- `bmi` has 1462 (3.37%) missing values
- `smoking_status` has 13292 (30.63%) missing values
- `hypertension` has constant length 1
- `heart_disease` has constant length 1
- `Residence_type` has constant length 5
- `stroke` has constant length 1

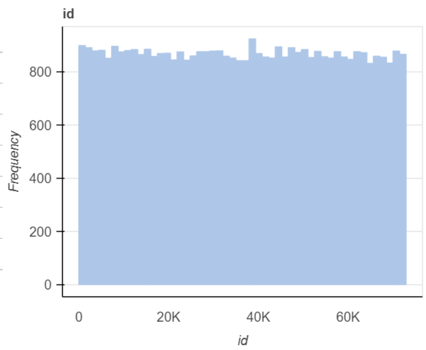
Variables

Sort by Feature order Reverse order

id
numerical
Show Details

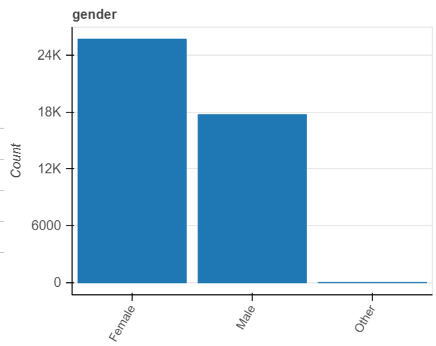
Approximate Distinct Count	43400
Approximate Unique (%)	100.0%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Memory Size	678.1 KB

Mean	36326.1424
Minimum	1
Maximum	72943
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%



gender
categorical
Show Details

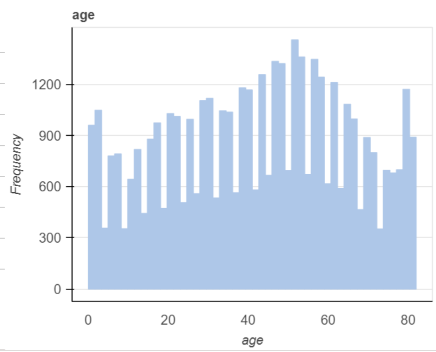
Approximate Distinct Count	3
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2.9 MB



age
numerical
Show Details

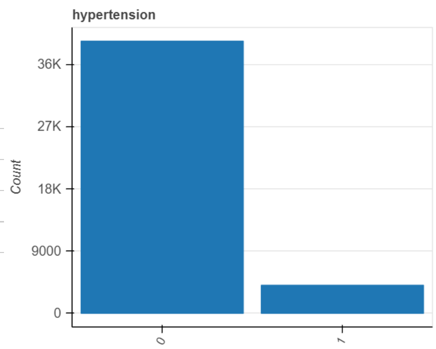
Approximate Distinct Count	104
Approximate Unique (%)	0.2%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Memory Size	678.1 KB

Mean	42.2179
Minimum	0.08
Maximum	82
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%



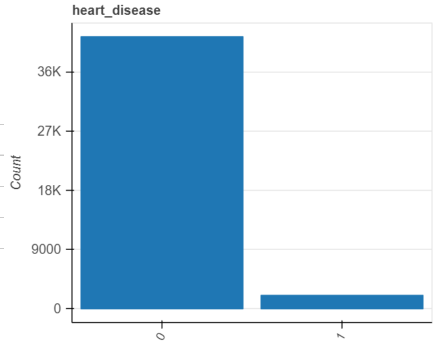
hypertension
categorical
Show Details

Approximate Distinct Count	2
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2.7 MB



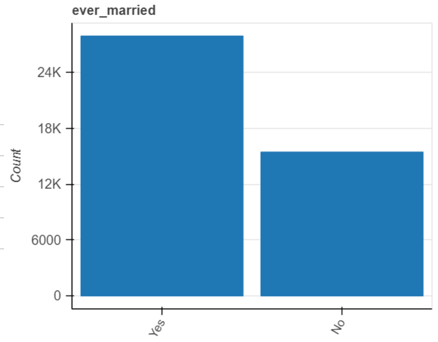
heart_disease
categorical
Show Details

Approximate Distinct Count	2
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2.7 MB



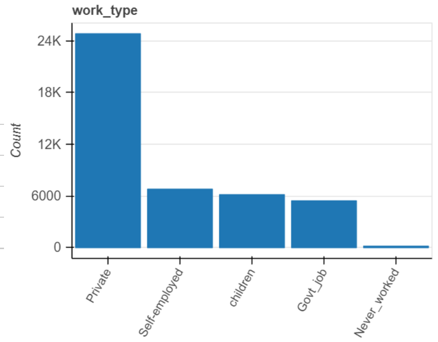
ever_married
categorical
Show Details

Approximate Distinct Count	2
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2.8 MB



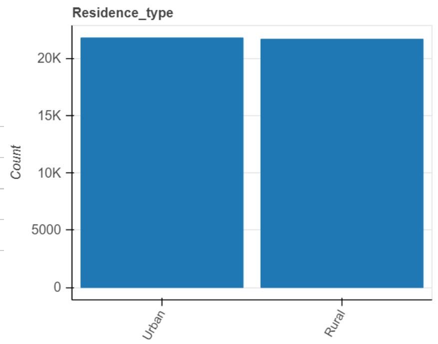
work_type
categorical
Show Details

Approximate Distinct Count	5
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	3.0 MB



Residence_type
categorical
Show Details

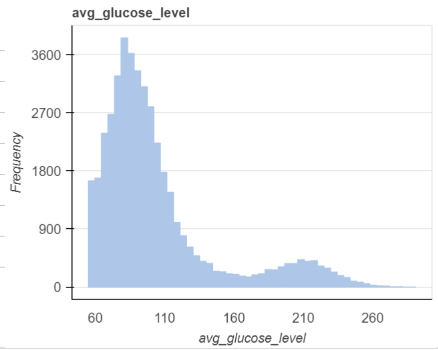
Approximate Distinct Count	2
Approximate Unique (%)	0.0%
Missing	0
Missing (%)	0.0%
Memory Size	2.9 MB



avg_glucose_level
numerical
Show Details

Approximate Distinct Count	12543
Approximate Unique (%)	28.9%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Memory Size	678.1 KB

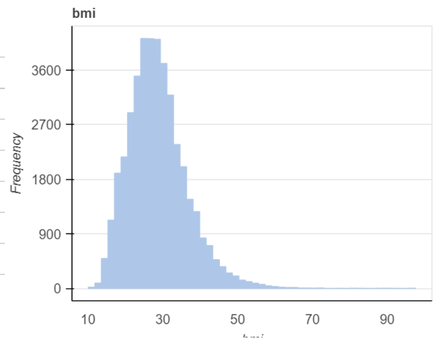
Mean	104.4827
Minimum	55
Maximum	291.05
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%



bmi
numerical
Show Details

Approximate Distinct Count	555
Approximate Unique (%)	1.3%
Missing	1462
Missing (%)	3.4%
Infinite	0
Infinite (%)	0.0%
Memory Size	655.3 KB

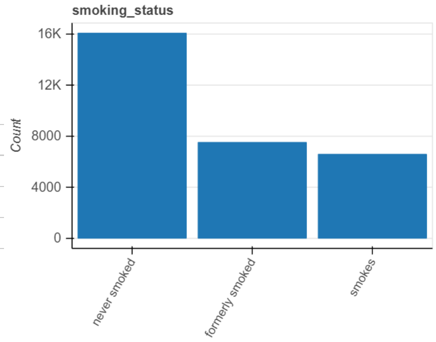
Mean	28.605
Minimum	10.1
Maximum	97.6
Zeros	0
Zeros (%)	0.0%
Negatives	0
Negatives (%)	0.0%



bmi

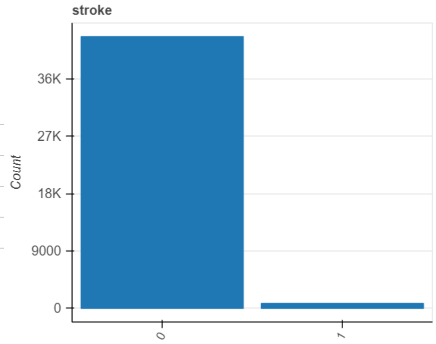
smoking_status
categorical
Show Details

Approximate Distinct Count	**3**
Approximate Unique (%)	**0.0%**
Missing	**13292**
Missing (%)	**30.6%**
Memory Size	**2.2 MB**



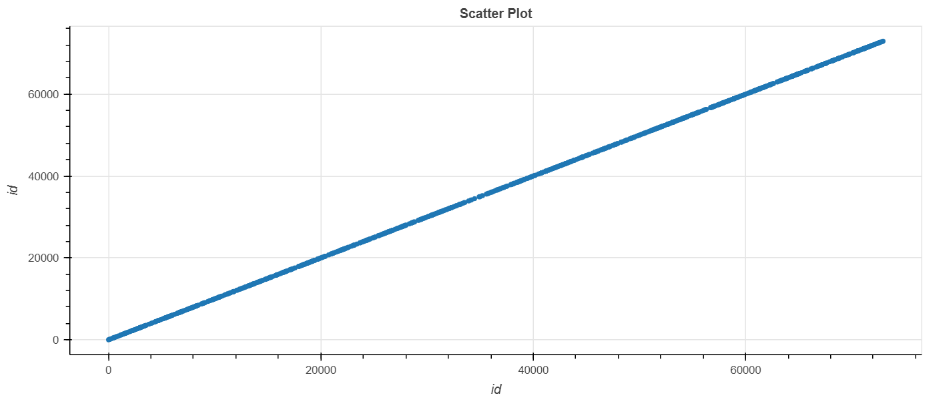
stroke
categorical
Show Details

Approximate Distinct Count	**2**
Approximate Unique (%)	**0.0%**
Missing	**0**
Missing (%)	**0.0%**
Memory Size	**2.7 MB**



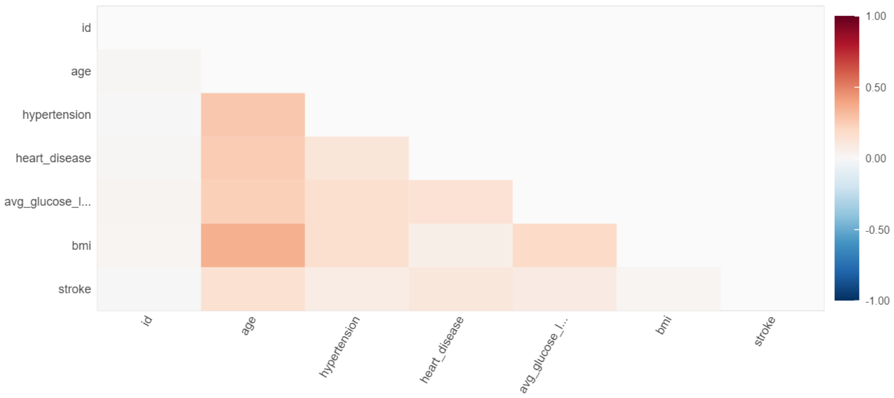
Interactions

X-Axis Y-Axis
id id



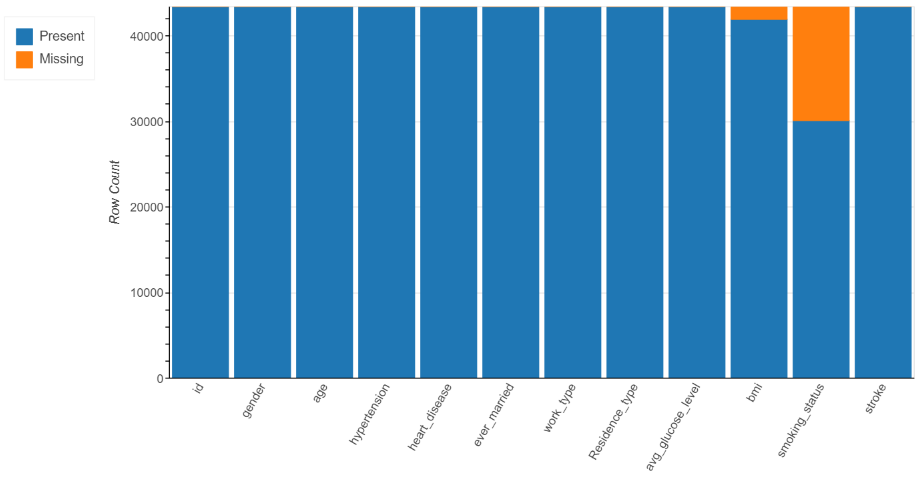
Correlations

Pearson Spearman KendallTau



Missing Values

Bar Chart Spectrum Heat Map Dendrogram



Report generated with DataPrep (https://dataprep.ai/)

In [ ]:
```
data.describe()
```

Out[ ]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	43400.000000	43400.000000	43400.000000	43400.000000	43400.000000	41938.000000	43400.000000
mean	36326.142350	42.217894	0.093571	0.047512	104.482750	28.605038	0.018041
std	21072.134879	22.519649	0.291235	0.212733	43.111751	7.770020	0.133103
min	1.000000	0.080000	0.000000	0.000000	55.000000	10.100000	0.000000
25%	18038.500000	24.000000	0.000000	0.000000	77.540000	23.200000	0.000000
50%	36351.500000	44.000000	0.000000	0.000000	91.580000	27.700000	0.000000
75%	54514.250000	60.000000	0.000000	0.000000	112.070000	32.900000	0.000000
max	72943.000000	82.000000	1.000000	1.000000	291.050000	97.600000	1.000000

From above description, we get that the number of rows and columns are 43400 and 12 respectively. There are some missing values (indicated by NaN). Now, we want to check how many missing values exist in each variable.

In [ ]:
```
miss_val = data.isnull().sum()/len(data)*100
print(miss_val)
print("# Missing values in variable bmi\t\t: {:.2f}%".format(miss_val['bmi']))
print("# Missing values in variable smoking_status\t: {:.2f}%".format(miss_val['smoking_status']))
print("Data shape: {}".format(data.shape))
```

```
id                    0.000000
gender                0.000000
age                   0.000000
hypertension          0.000000
heart_disease         0.000000
ever_married          0.000000
work_type             0.000000
Residence_type        0.000000
avg_glucose_level     0.000000
bmi                   3.368664
smoking_status       30.626728
stroke                0.000000
dtype: float64
# Missing values in variable bmi                : 3.37%
# Missing values in variable smoking_status     : 30.63%
Data shape: (43400, 12)
```

There are two variables that contain missing values. Firstly, the 'bmi' accounting to 3.37% of overal samples and secondly, the 'smoking_status' accounting to 30.63% of overall samples. To handle these missing values, we will remove the samples from all the variables associated with the indices of missing values in 'smoking_status'. For missing values in 'bmi' variable, we will replace them with the average of 'bmi' values.

In [ ]:
```
plot_missing(data)
```

Out[ ]:

Stats | Bar Chart | Spectrum | Heat Map | Dendrogram

Missing Statistics

Missing Cells	14754
Missing Cells (%)	2.8%
Missing Columns	2
Missing Rows	14328
Avg Missing Cells per Column	1229.5
Avg Missing Cells per Row	0.34

HANDLING MISSING VALUES

In [ ]:
```
# Safely disable new warning with the chained assignment.
pd.options.mode.chained_assignment = None  # default='warn'
# replace missing values in variable 'bmi' with its mean
data['bmi']=data['bmi'].fillna(data['bmi'].mean())
# remove (drop) data associated with missing values in variable 'smoking_status'
clean_data = data[data['smoking_status'].notnull()]
# drop variable 'id'
clean_data.drop(columns='id',axis=1,inplace=True)
# validate there's no more missing values
miss_val = clean_data.isnull().sum()/len(clean_data)*100
print(miss_val)
print("# Missing values in variable 'bmi'\t\t: {}".format(miss_val['bmi']))
print("# Missing values in variable 'smoking_status'\t: {}".format(miss_val['smoking_status']))
print("Shape of data without missing values: {}".format(clean_data.shape))
```

```
gender               0.0
age                  0.0
hypertension         0.0
heart_disease        0.0
ever_married         0.0
work_type            0.0
Residence_type       0.0
avg_glucose_level    0.0
bmi                  0.0
smoking_status       0.0
stroke               0.0
dtype: float64
# Missing values in variable 'bmi'              : 0.0
# Missing values in variable 'smoking_status'   : 0.0
Shape of data without missing values: (30108, 11)
```

CHANGING CATEGORY TO NUMERICAL VALUES

As some values as categorial we will have to change them to numerical ones

In [ ]:
```
print("Unique 'gender': {}".format(clean_data['gender'].unique()))
print("Unique 'ever_married': {}".format(clean_data['ever_married'].unique()))
print("Unique 'work_type': {}".format(clean_data['work_type'].unique()))
print("Unique 'Residence_type': {}".format(clean_data['Residence_type'].unique()))
print("Unique 'smoking_status': {}".format(clean_data['smoking_status'].unique()))
```

```
Unique 'gender': ['Male' 'Female' 'Other']
Unique 'ever_married': ['Yes' 'No']
Unique 'work_type': ['Private' 'Self-employed' 'Govt_job' 'children' 'Never_worked']
Unique 'Residence_type': ['Urban' 'Rural']
Unique 'smoking_status': ['never smoked' 'formerly smoked' 'smokes']
```

In [ ]:
```
# create encoder for each categorical variable
label_gender = LabelEncoder()
label_married = LabelEncoder()
label_work = LabelEncoder()
label_residence = LabelEncoder()
label_smoking = LabelEncoder()
```

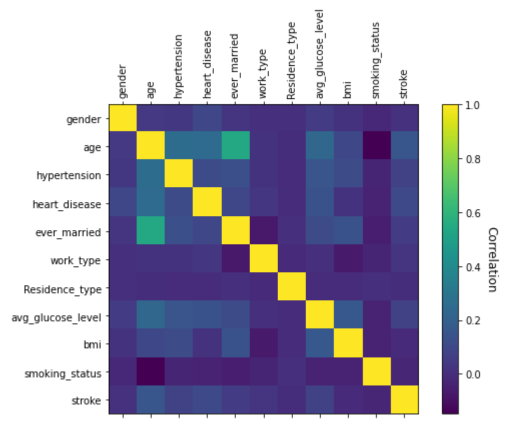
In [ ]:
```
clean_data['gender'] = label_gender.fit_transform(clean_data['gender'])
clean_data['ever_married'] = label_married.fit_transform(clean_data['ever_married'])
clean_data['work_type']= label_work.fit_transform(clean_data['work_type'])
clean_data['Residence_type']= label_residence.fit_transform(clean_data['Residence_type'])
clean_data['smoking_status']= label_smoking.fit_transform(clean_data['smoking_status'])
with pd.option_context('expand_frame_repr', False):
    print(clean_data.head())
```

```
   gender   age  hypertension  heart_disease  ever_married  work_type  Residence_type  avg_glucose_level   bmi  smoking_status  stroke
1       1  58.0             1              0             1          2               1              87.96  39.2               1       0
3       0  70.0             0              0             1          2               0              69.04  35.9               1       0
6       0  52.0             0              0             1          2               1              77.59  17.7               0       0
7       0  75.0             0              1             1          3               0             243.53  27.0               1       0
8       0  32.0             0              0             1          2               0              77.67  32.3               2       0
```

INTER-FEATURE CORRELATION

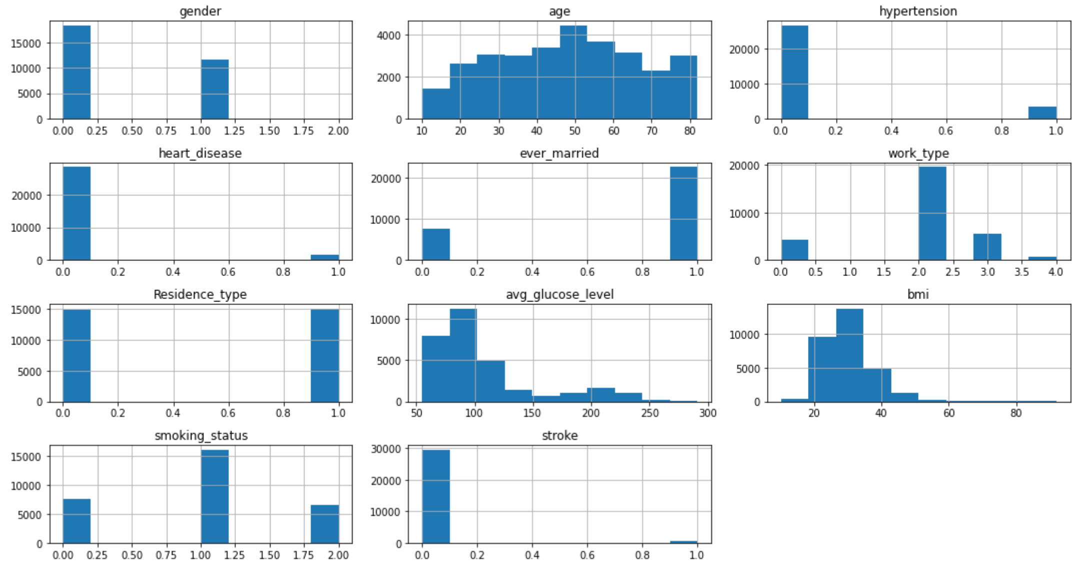
It is sometimes useful to measure the inter-feature correlation. If we find that a feature is highly correlated with the class (target), it could be an indication that this feature is informative about the class. In addition, if a feature is highly correlated with other features, we could remove one of them thus reducing the complexity while potentially improving the model's learning.

In [ ]:
```
fig, ax = plt.subplots(figsize=(8,6))
im = ax.matshow(clean_data.corr())
ax.set_xticks(np.arange(clean_data.shape[1]))
ax.set_yticks(np.arange(clean_data.shape[1]))
ax.set_xticklabels(clean_data.columns,rotation=90)
ax.set_yticklabels(clean_data.columns)
# Create colorbar
cbar = ax.figure.colorbar(im, ax=ax)
cbar.ax.set_ylabel("Correlation", rotation=-90, va="bottom", fontsize=12)
fig.tight_layout()
plt.show()
```



HISTOGRAM OF FEATURES

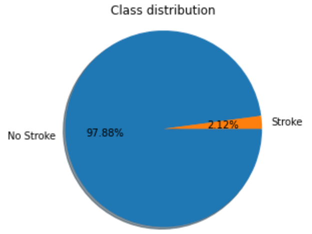
In [ ]:
```
fig = clean_data.hist(figsize=(15,8))
plt.tight_layout()
plt.show()
```



CLASS (TARGET) DISTRIBUTION

Now, let's have a look at the distribution of class. If the class is highly imbalanced, we have to solve this issue so that our model will not be biased towards the majority class.

In [ ]:
```
class_occur = clean_data['stroke'].value_counts()
class_names = ['No Stroke','Stroke']
fig, ax = plt.subplots()
ax.pie(class_occur, labels=class_names, autopct='%1.2f%%',
        shadow=True, startangle=0, counterclock=False)
ax.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
ax.set_title('Class distribution')
plt.show()
print("# samples associated with no stroke: {}".format(class_occur[0]))
print("# samples associated with stroke: {}".format(class_occur[1]))
```




```
# samples associated with no stroke: 29470
# samples associated with stroke: 638
```

DATA PREPROCESSING

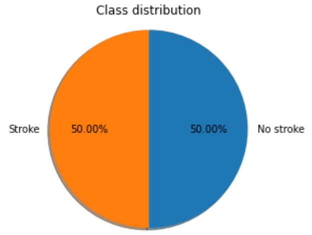
HANDLING IMBALANCED CLASS

There are several techniques that can be used to handle highly imbalanced class. This article nicely summarises those different techniques. In this notebook, we are going to use one of oversampling technique called Synthetic Minority Oversampling Technique (SMOTE), by synthesising new samples from the minority class to have the same number of samples as the majority class (illustrated in figure below). Oversampling technique is chosen because we do not want to loose significant amount of information (97.88%) as if we use undersampling technique.

In [ ]:
```
smote = SMOTE(sampling_strategy='minority')

# fit the object to our training data
X, y = smote.fit_resample(clean_data.loc[:,clean_data.columns!='stroke'], clean_data['stroke'])
print("Shape of X: {}".format(X.shape))
print("Shape of y: {}".format(y.shape))
```

```
Shape of X: (58940, 10)
Shape of y: (58940,)
```

In [ ]:
```
_, class_counts = np.unique(y, return_counts=True)
class_names = ['No stroke', 'Stroke']
fig, ax = plt.subplots()
ax.pie(class_counts, labels=class_names, autopct='%1.2f%%',
        shadow=True, startangle=90, counterclock=False)
ax.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
ax.set_title('Class distribution')
plt.show()
print("# samples associated with no stroke: {}".format(class_counts[0]))
print("# samples associated with stroke: {}".format(class_counts[1]))
```




```
# samples associated with no stroke: 29470
# samples associated with stroke: 29470
```

DATA SPLITTING

In [ ]:
```
def split_train_valid_test(X,y,test_size=0.1,random_state=None):
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=test_size, random_state=random_state, stratify=y)
    X_train, X_valid, y_train, y_valid = train_test_split(X_train,y_train,test_size=test_size/(1-test_size), random_state=random_state, stratify=y_train)
    return X_train, X_valid, X_test, y_train, y_valid, y_test

X_train, X_valid, X_test, y_train, y_valid, y_test = split_train_valid_test(X,y,test_size=0.1,random_state=42)
_, train_counts = np.unique(y_train, return_counts=True)
_, valid_counts = np.unique(y_valid, return_counts=True)
_, test_counts = np.unique(y_test, return_counts=True)
print("[train] # class 0: {} | # class 1: {}".format(train_counts[0],train_counts[1]))
print("[valid] # class 0: {} | # class 1: {}".format(valid_counts[0],valid_counts[1]))
print("[test]  # class 0: {} | # class 1: {}".format(test_counts[0],test_counts[1]))
```

```
[train] # class 0: 23576 | # class 1: 23576
[valid] # class 0: 2947 | # class 1: 2947
[test]  # class 0: 2947 | # class 1: 2947
```

DATA NORMALIZING

In [ ]:
```
scaler = StandardScaler()
scaler = scaler.fit(X_train)

X_train_std = scaler.transform(X_train)
X_valid_std = scaler.transform(X_valid)
X_test_std = scaler.transform(X_test)
```

MODEL TRAINING AND EVALUATION OF MACHINE LEARNING ALGORITHMS

Now we will be implementing and benchmarking the performance of the following ML algorithms:

PERFORMANCE METRICS

The peformance will be evaluated based on two different groups of metrics:

1. *Sensitivity, specificity, and area under the curve (AUC)*
2. *Precision, recall, and F1 score*

In [ ]:
```
def calc_sens_spec(y_true,y_pred):
    conf_matrix = confusion_matrix(y_true,y_pred)
    TP = conf_matrix[1][1]
    TN = conf_matrix[0][0]
    FP = conf_matrix[0][1]
    FN = conf_matrix[1][0]
    # calculate the sensitivity
    sensitivity = TP / (TP + FN)
    # calculate the specificity
    specificity = TN / (TN + FP)
    return sensitivity,specificity
```

SUPPORT VECTOR MACHINE (SVM)

In [ ]:
```
start = timer.time()
svm_model = SVC(kernel='rbf',probability=True)
svm_model.fit(X_train_std, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_svm = svm_model.predict(X_test_std)
y_svm_prob = svm_model.predict_proba(X_test_std)
```

```
Finished training within 312.75 seconds
```

In [ ]:
```
print("Classification report for SVM: \n{}".format(classification_report(y_test,y_svm)))
print("Confusion matrix for SVM: \n{}".format(confusion_matrix(y_test,y_svm)))
print("Accuracy score for SVM: {:.2f}".format(accuracy_score(y_test,y_svm)))
```

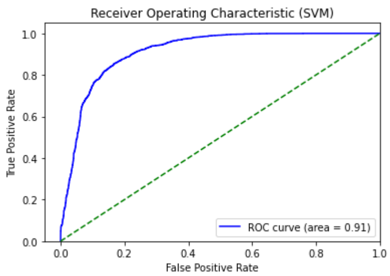
```
Classification report for SVM: 
              precision    recall  f1-score   support

           0       0.87      0.80      0.83      2947
           1       0.81      0.88      0.85      2947

    accuracy                           0.84      5894
   macro avg       0.84      0.84      0.84      5894
weighted avg       0.84      0.84      0.84      5894

Confusion matrix for SVM: 
[[2352  595]
 [ 350 2597]]
Accuracy score for SVM: 0.84
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_svm = precision_score(y_test,y_svm)
rec_svm = recall_score(y_test,y_svm)
f1_svm = f1_score(y_test,y_svm)
print("Precision score for SVM: {:.2f}".format(prec_svm))
print("Recall score for SVM: {:.2f}".format(rec_svm))
print("F1 score for SVM: {:.2f}".format(f1_svm))
```

```
Precision score for SVM: 0.81
Recall score for SVM: 0.88
F1 score for SVM: 0.85
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_svm,spec_svm = calc_sens_spec(y_test,y_svm)
fpr, tpr, _ = roc_curve(y_test,  y_svm_prob[:,1])
auc_svm = roc_auc_score(y_test, y_svm_prob[:,1])
print("Sensitivity score for SVM: {:.2f}".format(sens_svm))
print("Specitivity score for SVM: {:.2f}".format(spec_svm))
print("AUC score for SVM: {:.2f}".format(auc_svm))
fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_svm)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (SVM)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for SVM: 0.88
Specitivity score for SVM: 0.80
AUC score for SVM: 0.91
```



GAUSSIAN NAIVE BAYES (GNB)

In [ ]:
```
start = timer.time()
gnb_model = GaussianNB()
gnb_model.fit(X_train_std, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_gnb = gnb_model.predict(X_test_std)
y_gnb_prob = gnb_model.predict_proba(X_test_std)
```

```
Finished training within 0.01 seconds
```

In [ ]:
```
print("Classification report for GNB: \n{}".format(classification_report(y_test,y_gnb)))
print("Confusion matrix for GNB: \n{}".format(confusion_matrix(y_test,y_gnb)))
print("Accuracy score for GNB: {:.2f}".format(accuracy_score(y_test,y_gnb)))
```

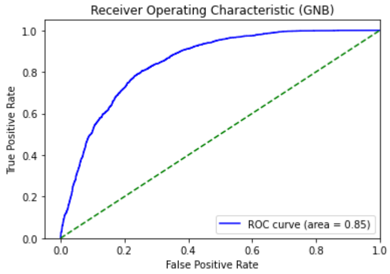
```
Classification report for GNB: 
              precision    recall  f1-score   support

           0       0.80      0.73      0.76      2947
           1       0.75      0.81      0.78      2947

    accuracy                           0.77      5894
   macro avg       0.77      0.77      0.77      5894
weighted avg       0.77      0.77      0.77      5894

Confusion matrix for GNB: 
[[2154  793]
 [ 554 2393]]
Accuracy score for GNB: 0.77
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_gnb = precision_score(y_test,y_gnb)
rec_gnb = recall_score(y_test,y_gnb)
f1_gnb = f1_score(y_test,y_gnb)
print("Precision score for GNB: {:.2f}".format(prec_gnb))
print("Recall score for GNB: {:.2f}".format(rec_gnb))
print("F1 score for GNB: {:.2f}".format(f1_gnb))
```

```
Precision score for GNB: 0.75
Recall score for GNB: 0.81
F1 score for GNB: 0.78
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_gnb,spec_gnb = calc_sens_spec(y_test,y_gnb)
fpr, tpr, _ = roc_curve(y_test,  y_gnb_prob[:,1])
auc_gnb = roc_auc_score(y_test, y_gnb_prob[:,1])
print("Sensitivity score for GNB: {:.2f}".format(sens_gnb))
print("Specitivity score for GNB: {:.2f}".format(spec_gnb))
print("AUC score for GNB: {:.2f}".format(auc_gnb))
fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_gnb)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (GNB)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for GNB: 0.81
Specitivity score for GNB: 0.73
AUC score for GNB: 0.85
```



LOGISTIC REGRESSION (LR)

In [ ]:
```
start = timer.time()
logit_model = LogisticRegression(solver='lbfgs', random_state=42)
logit_model.fit(X_train_std, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_logit = logit_model.predict(X_test_std)
y_logit_prob = logit_model.predict_proba(X_test_std)
```

```
Finished training within 0.06 seconds
```

In [ ]:
```
print("Classification report for LR: \n{}".format(classification_report(y_test,y_logit)))
print("Confusion matrix for LR: \n{}".format(confusion_matrix(y_test,y_logit)))
print("Accuracy score for LR: {:.2f}".format(accuracy_score(y_test,y_logit)))
```

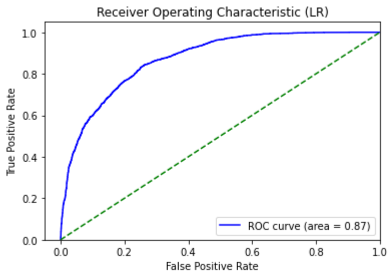
```
Classification report for LR:
              precision    recall  f1-score   support

           0       0.80      0.76      0.78      2947
           1       0.77      0.81      0.79      2947

    accuracy                           0.79      5894
   macro avg       0.79      0.79      0.79      5894
weighted avg       0.79      0.79      0.79      5894

Confusion matrix for LR:
[[2244  703]
 [ 559 2388]]
Accuracy score for LR: 0.79
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_logit = precision_score(y_test,y_logit)
rec_logit = recall_score(y_test,y_logit)
f1_logit = f1_score(y_test,y_logit)

print("Precision score for LR: {:.2f}".format(prec_logit))
print("Recall score for LR: {:.2f}".format(rec_logit))
print("F1 score for LR: {:.2f}".format(f1_logit))
```

```
Precision score for LR: 0.77
Recall score for LR: 0.81
F1 score for LR: 0.79
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_logit,spec_logit = calc_sens_spec(y_test,y_logit)
fpr, tpr, _ = roc_curve(y_test,  y_logit_prob[:,1])
auc_logit = roc_auc_score(y_test, y_logit_prob[:,1])

print("Sensitivity score for LR: {:.2f}".format(sens_logit))
print("Specitivity score for LR: {:.2f}".format(spec_logit))
print("AUC score for LR: {:.2f}".format(auc_logit))

fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_logit)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (LR)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for LR: 0.81
Specitivity score for LR: 0.76
AUC score for LR: 0.87
```



DECISION TREE (DT)

In [ ]:
```
start = timer.time()
dtree_model = DecisionTreeClassifier(random_state=42)
dtree_model.fit(X_train_std, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_dtree = dtree_model.predict(X_test_std)
y_dtree_prob = dtree_model.predict_proba(X_test_std)
```

```
Finished training within 0.25 seconds
```

In [ ]:
```
print("Classification report for DT: \n{}".format(classification_report(y_test,y_dtree)))
print("Confusion matrix for DT: \n{}".format(confusion_matrix(y_test,y_dtree)))
print("Accuracy score for DT: {:.2f}".format(accuracy_score(y_test,y_dtree)))
```

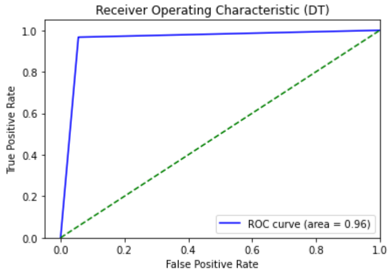
```
Classification report for DT:
              precision    recall  f1-score   support

           0       0.97      0.94      0.96      2947
           1       0.95      0.97      0.96      2947

    accuracy                           0.96      5894
   macro avg       0.96      0.96      0.96      5894
weighted avg       0.96      0.96      0.96      5894

Confusion matrix for DT:
[[2783  164]
 [  98 2849]]
Accuracy score for DT: 0.96
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_dtree = precision_score(y_test,y_dtree)
rec_dtree = recall_score(y_test,y_dtree)
f1_dtree = f1_score(y_test,y_dtree)

print("Precision score for DT: {:.2f}".format(prec_dtree))
print("Recall score for DT: {:.2f}".format(rec_dtree))
print("F1 score for DT: {:.2f}".format(f1_dtree))
```

```
Precision score for DT: 0.95
Recall score for DT: 0.97
F1 score for DT: 0.96
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_dtree,spec_dtree = calc_sens_spec(y_test,y_dtree)
fpr, tpr, _ = roc_curve(y_test,  y_dtree_prob[:,1])
auc_dtree = roc_auc_score(y_test, y_dtree_prob[:,1])

print("Sensitivity score for DT: {:.2f}".format(sens_dtree))
print("Specitivity score for DT: {:.2f}".format(spec_dtree))
print("AUC score for DT: {:.2f}".format(auc_dtree))

fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_dtree)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (DT)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for DT: 0.97
Specitivity score for DT: 0.94
AUC score for DT: 0.96
```



RANDOM FOREST ALGORITHM (RFA)

In [ ]:
```
start = timer.time()
ranfor_model = RandomForestClassifier(n_estimators=100, random_state=42)
ranfor_model.fit(X_train_std, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_ranfor = ranfor_model.predict(X_test_std)
y_ranfor_prob = ranfor_model.predict_proba(X_test_std)
```

```
Finished training within 5.49 seconds
```

In [ ]:
```
print("Classification report for RF: \n{}".format(classification_report(y_test,y_ranfor)))
print("Confusion matrix for RF: \n{}".format(confusion_matrix(y_test,y_ranfor)))
print("Accuracy score for RF: {:.2f}".format(accuracy_score(y_test,y_ranfor)))
```

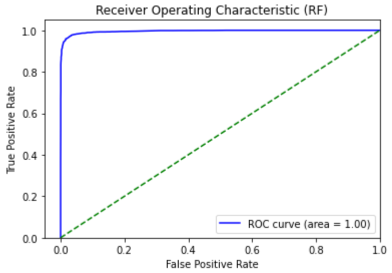
```
Classification report for RF:
              precision    recall  f1-score   support

           0       0.98      0.96      0.97      2947
           1       0.96      0.98      0.97      2947

    accuracy                           0.97      5894
   macro avg       0.97      0.97      0.97      5894
weighted avg       0.97      0.97      0.97      5894

Confusion matrix for RF:
[[2828  119]
 [  62 2885]]
Accuracy score for RF: 0.97
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_ranfor = precision_score(y_test,y_ranfor)
rec_ranfor = recall_score(y_test,y_ranfor)
f1_ranfor = f1_score(y_test,y_ranfor)

print("Precision score for RF: {:.2f}".format(prec_ranfor))
print("Recall score for RF: {:.2f}".format(rec_ranfor))
print("F1 score for RF: {:.2f}".format(f1_ranfor))
```

```
Precision score for RF: 0.96
Recall score for RF: 0.98
F1 score for RF: 0.97
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_ranfor,spec_ranfor = calc_sens_spec(y_test,y_ranfor)
fpr, tpr, _ = roc_curve(y_test,  y_ranfor_prob[:,1])
auc_ranfor = roc_auc_score(y_test, y_ranfor_prob[:,1])

print("Sensitivity score for RF: {:.2f}".format(sens_ranfor))
print("Specitivity score for RF: {:.2f}".format(spec_ranfor))
print("AUC score for RF: {:.2f}".format(auc_ranfor))

fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_ranfor)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (RF)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for RF: 0.98
Specitivity score for RF: 0.96
AUC score for RF: 1.00
```



LightGBM (LGBM)

In [ ]:
```
start = timer.time()
lgbm_model = LGBMClassifier(n_estimators=100, random_state=42)
lgbm_model.fit(X_train_std, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_lgbm = lgbm_model.predict(X_test_std)
y_lgbm_prob = lgbm_model.predict_proba(X_test_std)
```

```
Finished training within 0.48 seconds
```

In [ ]:
```
print("Classification report for LGBM: \n{}".format(classification_report(y_test,y_lgbm)))
print("Confusion matrix for LGBM: \n{}".format(confusion_matrix(y_test,y_lgbm)))
print("Accuracy score for LGBM: {:.2f}".format(accuracy_score(y_test,y_lgbm)))
```

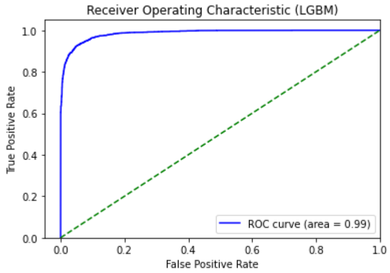
```
Classification report for LGBM:
              precision    recall  f1-score   support

           0       0.94      0.92      0.93      2947
           1       0.93      0.95      0.94      2947

    accuracy                           0.93      5894
   macro avg       0.94      0.93      0.93      5894
weighted avg       0.94      0.93      0.93      5894

Confusion matrix for LGBM:
[[2724  223]
 [ 161 2786]]
Accuracy score for LGBM: 0.93
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_lgbm = precision_score(y_test,y_lgbm)
rec_lgbm = recall_score(y_test,y_lgbm)
f1_lgbm = f1_score(y_test,y_lgbm)

print("Precision score for LGBM: {:.2f}".format(prec_lgbm))
print("Recall score for LGBM: {:.2f}".format(rec_lgbm))
print("F1 score for LGBM: {:.2f}".format(f1_lgbm))
```

```
Precision score for LGBM: 0.93
Recall score for LGBM: 0.95
F1 score for LGBM: 0.94
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_lgbm,spec_lgbm = calc_sens_spec(y_test,y_lgbm)
fpr, tpr, _ = roc_curve(y_test,  y_lgbm_prob[:,1])
auc_lgbm = roc_auc_score(y_test, y_lgbm_prob[:,1])

print("Sensitivity score for LGBM: {:.2f}".format(sens_lgbm))
print("Specitivity score for LGBM: {:.2f}".format(spec_lgbm))
print("AUC score for LGBM: {:.2f}".format(auc_lgbm))

fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_lgbm)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (LGBM)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for LGBM: 0.95
Specitivity score for LGBM: 0.92
AUC score for LGBM: 0.99
```



XGBoost (XGB)

In [ ]:
```
start = timer.time()
xgb_model = XGBClassifier(objective="binary:logistic", random_state=42)
xgb_model.fit(X_train_std, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_xgb = xgb_model.predict(X_test_std)
y_xgb_prob = xgb_model.predict_proba(X_test_std)
```

```
Finished training within 2.29 seconds
```

In [ ]:
```
print("Classification report for XGB: \n{}".format(classification_report(y_test,y_xgb)))
print("Confusion matrix for XGB: \n{}".format(confusion_matrix(y_test,y_xgb)))
print("Accuracy score for XGB: {:.2f}".format(accuracy_score(y_test,y_xgb)))
```

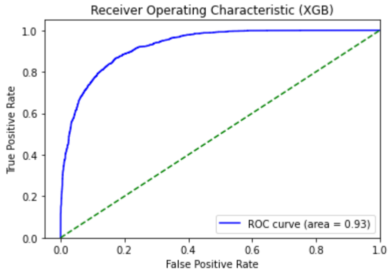
```
Classification report for XGB:
              precision    recall  f1-score   support

           0       0.87      0.81      0.84      2947
           1       0.82      0.88      0.85      2947

    accuracy                           0.84      5894
   macro avg       0.84      0.84      0.84      5894
weighted avg       0.84      0.84      0.84      5894

Confusion matrix for XGB:
[[2380  567]
 [ 363 2584]]
Accuracy score for XGB: 0.84
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_xgb = precision_score(y_test,y_xgb)
rec_xgb = recall_score(y_test,y_xgb)
f1_xgb = f1_score(y_test,y_xgb)

print("Precision score for XGB: {:.2f}".format(prec_xgb))
print("Recall score for XGB: {:.2f}".format(rec_xgb))
print("F1 score for XGB: {:.2f}".format(f1_xgb))
```

```
Precision score for XGB: 0.82
Recall score for XGB: 0.88
F1 score for XGB: 0.85
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_xgb,spec_xgb = calc_sens_spec(y_test,y_xgb)
fpr, tpr, _ = roc_curve(y_test,  y_xgb_prob[:,1])
auc_xgb = roc_auc_score(y_test, y_xgb_prob[:,1])

print("Sensitivity score for XGB: {:.2f}".format(sens_xgb))
print("Specitivity score for XGB: {:.2f}".format(spec_xgb))
print("AUC score for XGB: {:.2f}".format(auc_xgb))

fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_xgb)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (XGB)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for XGB: 0.88
Specitivity score for XGB: 0.81
AUC score for XGB: 0.93
```



K-NEAREST NEIGHBOUR (KNN)

In [ ]:
```
start = timer.time()
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))
# Predicting the test set results
y_KNC = classifier.fit(X_train, y_train).predict(X_test_std)
y_KNC_prob = classifier.fit(X_train, y_train).predict_proba(X_test_std)
```

```
Finished training within 0.08 seconds
```

In [ ]:
```
print("Classification report for KNN: \n{}".format(classification_report(y_test,y_KNC)))
print("Confusion matrix for KNN: \n{}".format(confusion_matrix(y_test,y_KNC)))
print("Accuracy score for KNN: {:.2f}".format(accuracy_score(y_test,y_KNC)))
```

```
Classification report for KNN: 
              precision    recall  f1-score   support

           0       0.50      1.00      0.67      2947
           1       0.00      0.00      0.00      2947

    accuracy                           0.50      5894
   macro avg       0.25      0.50      0.33      5894
weighted avg       0.25      0.50      0.33      5894

Confusion matrix for KNN: 
[[2947    0]
 [2947    0]]
Accuracy score for KNN: 0.50
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_KNC = precision_score(y_test,y_KNC)
print("Precision score for KNN: {:.2f}".format(prec_KNC))
```

```
Precision score for KNN: 0.00
```

In [ ]:
```
# calculate precision, recall, and f1 scores
rec_KNC = recall_score(y_test,y_KNC)
print("Recall score for KNN: {:.2f}".format(rec_KNC))
```

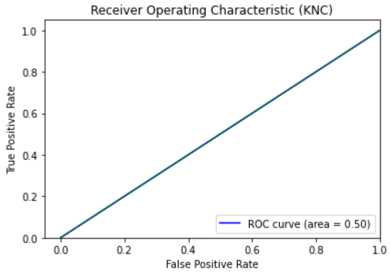
```
Recall score for KNN: 0.00
```

In [ ]:
```
# calculate precision, recall, and f1 scores
f1_KNC = f1_score(y_test,y_KNC)
print("F1 score for KNN: {:.2f}".format(f1_KNC))
```

```
F1 score for KNN: 0.00
```

In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_KNC,spec_KNC = calc_sens_spec(y_test,y_KNC)
fpr, tpr, _ = roc_curve(y_test,  y_KNC_prob[:,1])
auc_KNC = roc_auc_score(y_test, y_KNC_prob[:,1])

print("Sensitivity score for KNN: {:.2f}".format(sens_KNC))
print("Specitivity score for KNN: {:.2f}".format(spec_KNC))
print("AUC score for KNN: {:.2f}".format(auc_KNC))

fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_KNC)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (KNC)')
ax.legend(loc="lower right")
plt.show()
```

```
Sensitivity score for KNN: 0.00
Specitivity score for KNN: 1.00
AUC score for KNN: 0.50
```



SGD CLASSIFIER

In [ ]:
```
start = timer.time()
sgdc = SGDClassifier(max_iter=1000, tol=0.01)
sgdc.fit(X_train, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

# Predicting the test set results
y_sgdc = sgdc.fit(X_train, y_train).predict(X_test_std)
ypred = sgdc.predict(X_test)
```

```
Finished training within 1.93 seconds
```

In [ ]:
```
cr = classification_report(y_sgdc, ypred)
print(cr)
print("Accuracy score for sgdc: {:.2f}".format(accuracy_score(y_sgdc,ypred)))
```

```
              precision    recall  f1-score   support

           0       1.00      0.45      0.62      5894
           1       0.00      0.00      0.00         0

    accuracy                           0.45      5894
   macro avg       0.50      0.22      0.31      5894
weighted avg       1.00      0.45      0.62      5894

Accuracy score for sgdc: 0.45
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_sgdc = precision_score(y_test,y_sgdc)
rec_sgdc = recall_score(y_test,y_sgdc)
f1_sgdc = f1_score(y_test,y_sgdc)

print("Precision score for sgdc: {:.2f}".format(prec_sgdc))
print("Recall score for sgdc: {:.2f}".format(rec_sgdc))
print("F1 score for sgdc: {:.2f}".format(f1_sgdc))
```

```
Precision score for sgdc: 0.00
Recall score for sgdc: 0.00
F1 score for sgdc: 0.00
```

In [ ]:
```
# calculate sensitivity, specificity
sens_sgdc,spec_sgdc = calc_sens_spec(y_test,y_sgdc)
print("Sensitivity score for sgdc: {:.2f}".format(sens_sgdc))
print("Specitivity score for sgdc: {:.2f}".format(spec_sgdc))
```

```
Sensitivity score for sgdc: 0.00
Specitivity score for sgdc: 1.00
```

AdaBoost CLASSIFIER

In [ ]:
```
start = timer.time()
abc = AdaBoostClassifier(n_estimators=2000, random_state = 0)
model = abc.fit(X_train, y_train)
end = timer.time()
print("Finished training within {:.2f} seconds".format(end-start))

#Predict the response for test dataset
y_abc = model.predict(X_test_std)
y_abc_prob = model.predict_proba(X_test_std)
```

```
Finished training within 66.34 seconds
```

In [ ]:
```
print("AdaBoost Classifier Model Accuracy:", accuracy_score(y_test, y_abc))
```

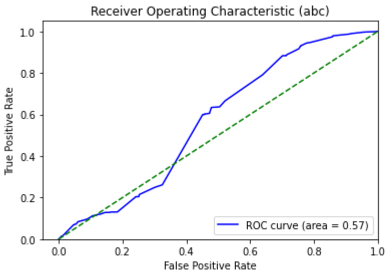
```
AdaBoost Classifier Model Accuracy: 0.5
```

In [ ]:
```
# calculate precision, recall, and f1 scores
prec_abc = precision_score(y_test,y_abc)
rec_abc = recall_score(y_test,y_abc)
f1_abc = f1_score(y_test,y_abc)

print("Precision score for XGB: {:.2f}".format(prec_abc))
print("Recall score for XGB: {:.2f}".format(rec_abc))
print("F1 score for XGB: {:.2f}".format(f1_abc))
```

```
Precision score for XGB: 0.00
Recall score for XGB: 0.00
F1 score for XGB: 0.00
```

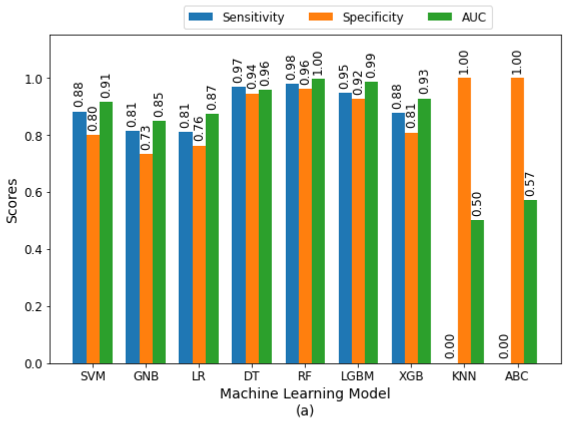
In [ ]:
```
# calculate sensitivity, specificity, and auc
sens_abc,spec_abc = calc_sens_spec(y_test,y_abc)
fpr, tpr, _ = roc_curve(y_test,  y_abc_prob[:,1])
auc_abc = roc_auc_score(y_test, y_abc_prob[:,1])

print("Sensitivity score for abc: {:.2f}".format(sens_abc))
print("Specitivity score for abc: {:.2f}".format(spec_abc))
print("AUC score for abc: {:.2f}".format(auc_abc))

fig, ax = plt.subplots()
ax.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' % auc_abc)
ax.plot([0, 1], [0, 1], color='green', linestyle='--')
ax.set_xlim([-0.05, 1.0])
ax.set_ylim([0.0, 1.05])
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate')
ax.set_title('Receiver Operating Characteristic (abc)')
ax.legend(loc="lower right")
plt.show()
```

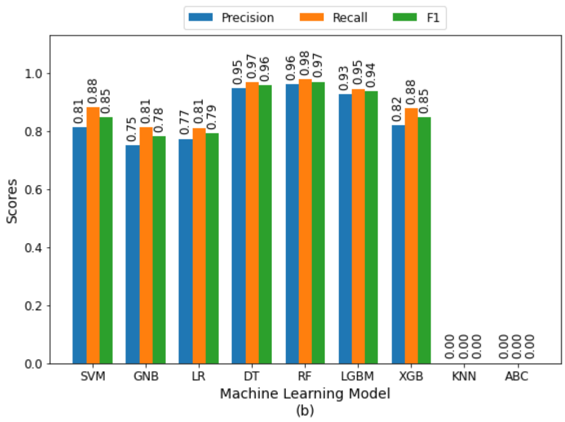
```
Sensitivity score for abc: 0.00
Specitivity score for abc: 1.00
AUC score for abc: 0.57
```



PERFORMANCE BENCHMARK ACROSS MODELS

In [ ]:
```
ml_names = ['SVM', 'GNB', 'LR', 'DT', 'RF', 'LGBM', 'XGB', 'KNN','ABC']
sens_all = [sens_svm, sens_gnb, sens_logit, sens_dtree, sens_ranfor, sens_lgbm, sens_xgb, sens_KNC, sens_abc]
spec_all = [spec_svm, spec_gnb, spec_logit, spec_dtree, spec_ranfor, spec_lgbm, spec_xgb, spec_KNC, spec_abc]
auc_all = [auc_svm, auc_gnb, auc_logit, auc_dtree, auc_ranfor, auc_lgbm, auc_xgb, auc_KNC, auc_abc]

prec_all = [prec_svm, prec_gnb, prec_logit, prec_dtree, prec_ranfor, prec_lgbm, prec_xgb, prec_KNC, prec_abc]
rec_all = [rec_svm, rec_gnb, rec_logit, rec_dtree, rec_ranfor, rec_lgbm, rec_xgb, rec_KNC, rec_abc]
f1_all = [f1_svm, f1_gnb, f1_logit, f1_dtree, f1_ranfor, f1_lgbm, f1_xgb, f1_KNC, f1_abc]

def autolabel(bars):
    """Attach a text label above each bar in displaying its height."""
    for bar in bars:
        height = bar.get_height()
        ax.annotate('{:.2f}'.format(height),
                    xy=(bar.get_x() + bar.get_width() / 2, height),
                    xytext=(0, 5),  # 3 points vertical offset
                    textcoords="offset points",
                    fontsize=12,
                    rotation=90,
                    ha='center', va='bottom')

width = 0.25  # the width of the bars
r1 = np.arange(len(ml_names))  # the label locations
r2 = [x + width for x in r1]
r3 = [x + width for x in r2]
# plot sensitivity, specificity, and auc
fig, ax = plt.subplots(figsize=(8,6))
bar1 = ax.bar(r1, sens_all, width, label='Sensitivity')
bar2 = ax.bar(r2, spec_all, width, label='Specificity')
bar3 = ax.bar(r3, auc_all, width, label='AUC')
# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylim([0,1.15])
ax.set_ylabel('Scores',fontsize=14)
#ax.set_title('Performance benchmark across ML models')
ax.set_xticks(r2)
ax.set_xticklabels(ml_names)
ax.tick_params(axis='both', which='major', labelsize=12)
ax.set_xlabel("Machine Learning Model\n(a)",fontsize=14)
ax.legend(loc='lower left',ncol=3,bbox_to_anchor=(0.25,1),fontsize=12)
autolabel(bar1)
autolabel(bar2)
autolabel(bar3)
fig.tight_layout()
fig.savefig("ml_benchmark_auc.pdf", bbox_inches='tight')
plt.show()

# plot sensitivity, specificity, and auc
fig, ax = plt.subplots(figsize=(8,6))
bar1 = ax.bar(r1, prec_all, width, label='Precision')
bar2 = ax.bar(r2, rec_all, width, label='Recall')
bar3 = ax.bar(r3, f1_all, width, label='F1')
# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylim([0,1.13])
ax.set_ylabel('Scores',fontsize=14)
#ax.set_title('Performance benchmark across ML models')
ax.set_xticks(r2)
ax.set_xticklabels(ml_names)
ax.tick_params(axis='both', which='major', labelsize=12)
ax.set_xlabel("Machine Learning Model\n(b)",fontsize=14)
ax.legend(loc='lower left',ncol=3,bbox_to_anchor=(0.25,1),fontsize=12)
autolabel(bar1)
autolabel(bar2)
autolabel(bar3)
fig.tight_layout()
fig.savefig("ml_benchmark_f1.pdf", bbox_inches='tight')
plt.show()
```





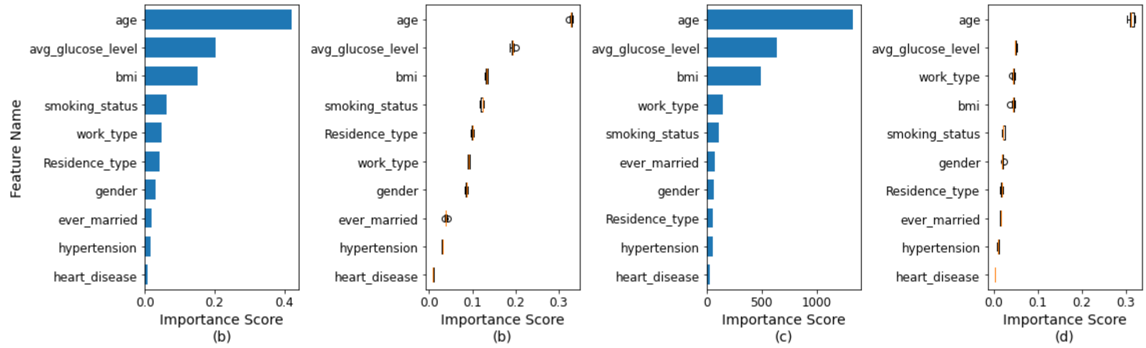
SELECTING MOST IMPORTANT FREATURES

To evaluate the most important features, we will use feature importance score which can be calculated using two different methods as follows:

1. *Tree based feature importance. This is calculated during the construction of the boosted decision trees within the model. The more an attribute is used to make key decisions with decision trees indicates higher relative importance. This can be access by using featureimportances attribute within the model.*
2. *Permutation based feature importance. First, we compute the baseline performance of the original trained model (without permutation) using the testing set; Second, for each feature, we permute the data in that feature, compute and record the performance based on the permuted data; lastly, compute the feature importance as the difference between the baseline performance and the performance based on the permuted data.*

In [ ]:

```
# feature importance from random forest
feature_names = clean_data.columns[:-1].to_numpy()
ranfor_perm_imp = permutation_importance(ranfor_model, X_test_std, y_test, n_repeats=10, random_state=42)
ranfor_perm_sort_idx = ranfor_perm_imp.importances_mean.argsort()

ranfor_tree_sort_idx = np.argsort(ranfor_model.feature_importances_)
ranfor_indices = np.arange(0, len(ranfor_model.feature_importances_)) + 0.5

fig, (ax1, ax2, ax3, ax4) = plt.subplots(1, 4, figsize=(16, 5))
ax1.barh(ranfor_indices,ranfor_model.feature_importances_[ranfor_tree_sort_idx], height=0.7)
ax1.tick_params(axis='both', which='major', labelsize=12)
ax1.set_xlabel("Importance Score\n(b)",fontsize=14)
ax1.set_ylabel("Feature Name",fontsize=14)
ax1.set_yticklabels(feature_names[ranfor_tree_sort_idx])
ax1.set_yticks(ranfor_indices)
ax1.set_ylim((0, len(ranfor_model.feature_importances_)))
ax2.boxplot(ranfor_perm_imp.importances[ranfor_perm_sort_idx].T,vert=False,labels=feature_names[ranfor_perm_sort_idx])
ax2.tick_params(axis='both', which='major', labelsize=12)
ax2.set_xlabel("Importance Score\n(b)",fontsize=14)


# feature importance from LGBM
lgbm_perm_imp = permutation_importance(lgbm_model, X_test_std, y_test, n_repeats=10, random_state=42)
lgbm_perm_sort_idx = lgbm_perm_imp.importances_mean.argsort()

lgbm_tree_sort_idx = np.argsort(lgbm_model.feature_importances_)
lgbm_indices = np.arange(0, len(lgbm_model.feature_importances_)) + 0.5

ax3.barh(lgbm_indices,lgbm_model.feature_importances_[lgbm_tree_sort_idx], height=0.7)
ax3.tick_params(axis='both', which='major', labelsize=12)
ax3.set_xlabel("Importance Score\n(c)",fontsize=14)
ax3.set_yticklabels(feature_names[lgbm_tree_sort_idx])
ax3.set_yticks(lgbm_indices)
ax3.set_ylim((0, len(lgbm_model.feature_importances_)))
ax4.boxplot(lgbm_perm_imp.importances[lgbm_perm_sort_idx].T,vert=False,labels=feature_names[lgbm_perm_sort_idx])
ax4.tick_params(axis='both', which='major', labelsize=12)
ax4.set_xlabel("Importance Score\n(d)",fontsize=14)


fig.tight_layout()
fig.savefig("feature_importance.pdf", bbox_inches='tight')
plt.show()
```



*In summary, two highest stroke prediction performance were achieved by **RANDOM FOREST and LGBM Algorithms** ; three most important features (in descending order) for stroke prediction were 'age', 'avg_glucose_level', and 'bmi'*