In [ ]:

In [2]:
```
import matplotlib.pyplot as plt
%matplotlib inline

import numpy as np
import seaborn as sns
import pandas as pd
pd.set_option("display.max_columns", 200)

import warnings
warnings.filterwarnings('ignore')
```

Read datasets from CSV

In [3]:
```
df = pd.read_csv("ids_data/attack_dataset.csv.gz") # attack dataset
bonafide = pd.read_csv('ids_data/bonafide_dataset_20191121.csv.gz') # bonafide t
bonafide = pd.concat([bonafide, pd.read_csv('ids_data/bonafide_dataset_20201110.
bonafide = pd.concat([bonafide, pd.read_csv('ids_data/bonafide_dataset_20201129.
```

In [4]:
```
# add label to bonafide dataset
bonafide['label'] = "bonafide"
```

compare both attack and bonafide datasets

In [5]:
```
# checking if both datasets have same columns count
if df.shape[1]==bonafide.shape[1]:
  print("Both datasets have the same number of columns")

print(df.shape)
print(bonafide.shape)
```

```
Both datasets have the same number of columns
(455503, 42)
(380438, 42)
```

In [6]:
```
# total number of records including attack and bonafide
total = df.shape[0] + bonafide.shape[0]
print(f"total number of records: {total}")

# total number of attack records
malicious = (df.shape[0]/total)*100
print("total % of attack records: {:0.2f}".format(malicious))

# total number of bonafide records
legitimate = (bonafide.shape[0]/total)*100
print("total % of bonafide records: {:0.2f}".format(legitimate))
```

```
total number of records: 835941
total % of attack records: 54.49
total % of bonafide records: 45.51
```

bonafide and attack dataset overview

In [7]:
```
df.head(3)
```

Out[7]:

	frame_info.encap_type	frame_info.time	frame_info.time_epoch	frame_info.number
0	1	Sep 2, 2020 21:04:37.063530000 -03	1.599091e+09	1
1	1	Sep 2, 2020 21:04:39.363792000 -03	1.599091e+09	2
2	1	Nov 16, 2020 18:15:14.851050000 -03	1.605561e+09	1

In [8]:
```
df.label.value_counts()
```

Out[8]:
```
label
zmap              74613
nmap_connect      45882
hping_syn         43750
unicorn_syn       43039
nmap_syn          40642
unicorn_conn      39170
masscan           21138
nmap_ack          20497
nmap_window       18851
nmap_null         12511
nmap_xmas         12505
nmap_fin          12504
hping_ack         11344
nmap_maimon       10493
unicorn_ack        8494
hping_xmas         7344
hping_null         7344
hping_fin          7344
unicorn_null       4690
unicorn_xmas       4466
unicorn_fxmas      4444
unicorn_fin        4438
Name: count, dtype: int64
```

In [9]:
```
bonafide.head(3)
```

Out[9]:

	frame_info.encap_type	frame_info.time	frame_info.time_epoch	frame_info.number
0	1	Nov 21, 2019 02:00:00.309420000 -03	1.574312e+09	2
1	1	Nov 21, 2019 02:00:00.313671000 -03	1.574312e+09	7
2	1	Nov 21, 2019 02:00:00.315642000 -03	1.574312e+09	10

In [10]:
```
bonafide.label.value_counts()
```

Out[10]:
```
label
bonafide    380438
Name: count, dtype: int64
```

combine both attack and bonafide datasets

In [11]:
```
full_data = pd.concat([bonafide, df])
```

Pre-processing

> converted features from hexadecimal to integer

> imputed null value fields by 0

In [12]:
```
hex_fields = ['eth.type', 'ip.id', 'ip.flags', 'ip.checksum', 'ip.dsfield', 'tcp

full_data = full_data.fillna(0)

for field in hex_fields:
    full_data[field] = full_data[field].apply(lambda x: int(str(x), 16))
```

In [13]:
```
print(full_data.shape)
```

```
(835941, 42)
```

check only packets with tcp protocol (ip proto 6) exist and filter other packets

In [14]:
```
non_tcp_records = full_data[full_data['ip.proto'] != 6].shape[0]
print("Removed", non_tcp_records,"non-tcp packets from the original dataset.")

# includes only the packets/records that are tcp-based
full_data = full_data[full_data['ip.proto'] == 6]
```

```
Removed 52177 non-tcp packets from the original dataset.
```

In [15]:
```
full_data.label.value_counts()
```

Out[15]:
```
label
bonafide         328261
zmap              74613
nmap_connect      45882
hping_syn         43750
unicorn_syn       43039
nmap_syn          40642
unicorn_conn      39170
masscan           21138
nmap_ack          20497
nmap_window       18851
nmap_null         12511
nmap_xmas         12505
nmap_fin          12504
hping_ack         11344
nmap_maimon       10493
unicorn_ack        8494
hping_xmas         7344
hping_null         7344
hping_fin          7344
unicorn_null       4690
unicorn_xmas       4466
unicorn_fxmas      4444
unicorn_fin        4438
Name: count, dtype: int64
```

Features that are irrelavant to my objective

> Removed layer-2 related features as below:
>
> - frame_info.time
> - frame_info.encap_type
> - frame_info.time_epoch
> - frame_info.number
> - frame_info.len
> - frame_info.cap_len
> - eth.type

> Removed reduntant or constant features as below:
>
> - ip.version - only IPV4 is taken now
> - ip.proto - only TCP records/packets are taken now
> - ip.src
> - ip.dst
> - ip.flags
> - tcp.flags

In [16]:
```
full_data.drop(columns=['frame_info.time', 'frame_info.encap_type', 'frame_info.
                        'frame_info.len', 'frame_info.cap_len', 'eth.type', 'ip.
                        'ip.version', 'ip.proto', 'tcp.flags'], axis=1, inplace=
```

Exploratory Data Analysis

In [17]:
```
full_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 783764 entries, 1 to 455502
Data columns (total 29 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   ip.hdr_len           783764 non-null  float64
 1   ip.tos               783764 non-null  float64
 2   ip.id                783764 non-null  int64  
 3   ip.flags.rb          783764 non-null  float64
 4   ip.flags.df          783764 non-null  float64
 5   ip.flags.mf          783764 non-null  float64
 6   ip.frag_offset       783764 non-null  float64
 7   ip.ttl               783764 non-null  float64
 8   ip.checksum          783764 non-null  int64  
 9   ip.len               783764 non-null  float64
 10  ip.dsfield           783764 non-null  int64  
 11  tcp.srcport          783764 non-null  float64
 12  tcp.dstport          783764 non-null  float64
 13  tcp.seq              783764 non-null  float64
 14  tcp.ack              783764 non-null  float64
 15  tcp.len              783764 non-null  float64
 16  tcp.hdr_len          783764 non-null  float64
 17  tcp.flags.fin        783764 non-null  float64
 18  tcp.flags.syn        783764 non-null  float64
 19  tcp.flags.reset      783764 non-null  float64
 20  tcp.flags.push       783764 non-null  float64
 21  tcp.flags.ack        783764 non-null  float64
 22  tcp.flags.urg        783764 non-null  float64
 23  tcp.flags.cwr        783764 non-null  float64
 24  tcp.window_size      783764 non-null  float64
 25  tcp.checksum         783764 non-null  int64  
 26  tcp.urgent_pointer   783764 non-null  float64
 27  tcp.options.mss_val  783764 non-null  float64
 28  label                783764 non-null  object 
dtypes: float64(24), int64(4), object(1)
memory usage: 179.4+ MB
```

In [18]:
```
full_data.describe()
```

Out[18]:

	ip.hdr_len	ip.tos	ip.id	ip.flags.rb	ip.flags.df	ip.flags.mf	ip
count	783764.0	783764.0	783764.000000	783764.0	783764.000000	783764.000000	
mean	20.0	0.0	30203.740695	0.0	0.645392	0.000003	
std	0.0	0.0	20375.832825	0.0	0.478395	0.001597	
min	20.0	0.0	0.000000	0.0	0.000000	0.000000	
25%	20.0	0.0	11779.000000	0.0	0.000000	0.000000	
50%	20.0	0.0	29827.000000	0.0	1.000000	0.000000	
75%	20.0	0.0	48693.000000	0.0	1.000000	0.000000	
max	20.0	0.0	65535.000000	0.0	1.000000	1.000000	

Removed columns with zero variance as they dont support learning

In [19]:
```
full_data.drop(columns=['label']).var() == 0
```

Out[19]:
```
ip.hdr_len              True
ip.tos                  True
ip.id                  False
ip.flags.rb             True
ip.flags.df            False
ip.flags.mf            False
ip.frag_offset          True
ip.ttl                 False
ip.checksum            False
ip.len                 False
ip.dsfield             False
tcp.srcport            False
tcp.dstport            False
tcp.seq                False
tcp.ack                False
tcp.len                False
tcp.hdr_len            False
tcp.flags.fin          False
tcp.flags.syn          False
tcp.flags.reset        False
tcp.flags.push         False
tcp.flags.ack          False
tcp.flags.urg          False
tcp.flags.cwr          False
tcp.window_size        False
tcp.checksum           False
tcp.urgent_pointer     False
tcp.options.mss_val    False
dtype: bool
```

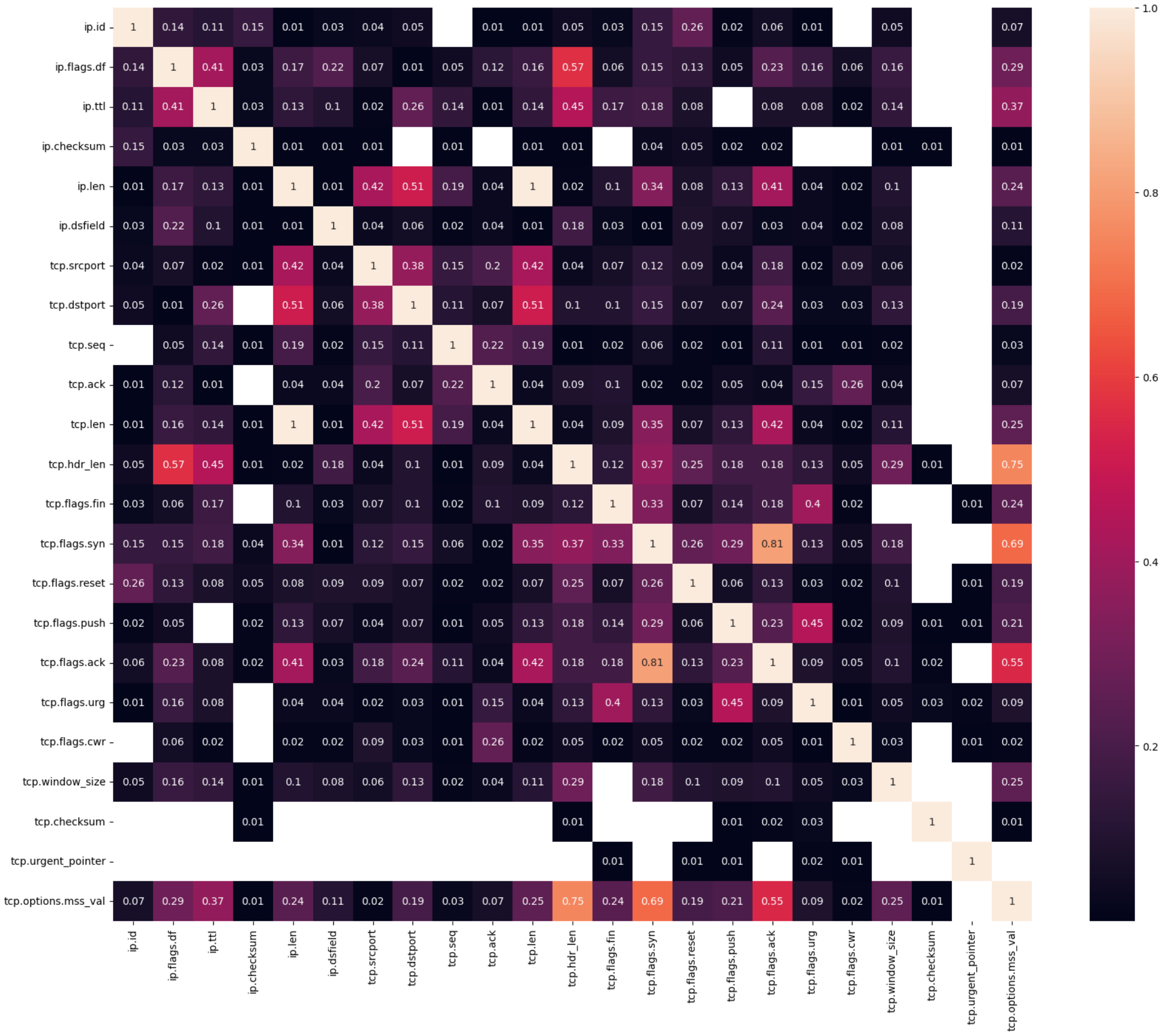
In [20]:
```
full_data.drop(columns=['ip.hdr_len', 'ip.tos', 'ip.flags.rb',
                         'ip.frag_offset', 'ip.flags.mf'], axis=1, inplace=True)
```

Linear Correlation greater than 0

In [21]:
```
corr_data = full_data.drop(columns=['label']).corr().abs().round(2)

# get only the features with positive correlation
corr_data = corr_data[corr_data>0]

plt.figure(figsize = (20,16))
sns.heatmap(corr_data, xticklabels=corr_data.columns, yticklabels=corr_data.colu
```



binary classification (attack or bonafide)

In [22]:
```
full_data['label'].value_counts()
```

Out[22]:
```
label
bonafide         328261
zmap              74613
nmap_connect      45882
hping_syn         43750
unicorn_syn       43039
nmap_syn          40642
unicorn_conn      39170
masscan           21138
nmap_ack          20497
nmap_window       18851
nmap_null         12511
nmap_xmas         12505
nmap_fin          12504
hping_ack         11344
nmap_maimon       10493
unicorn_ack        8494
hping_xmas         7344
hping_null         7344
hping_fin          7344
unicorn_null       4690
unicorn_xmas       4466
unicorn_fxmas      4444
unicorn_fin        4438
Name: count, dtype: int64
```

label encode the label column

> replace bonafide labels as 0

> replace attack lables as 1

In [23]:
```
full_data.label[full_data.label == "bonafide"] = 0
full_data.label[full_data.label != 0] = 1
full_data['label'].value_counts()
```

Out[23]:
```
label
1    455503
0    328261
Name: count, dtype: int64
```

In [24]:
```
full_data.shape
```

Out[24]:
```
(783764, 24)
```

Removal of some columns either random or might hinder learning

> - acknowledgement and cheksums are random
> - it is known tcp.dstport promotes learning the lab architecture where dataset was collected which is UNINTENDED

In [25]:
```
full_data.drop(columns=["ip.checksum", "tcp.checksum",
                        "tcp.ack", "tcp.dstport"], axis=1, inplace=True)
```

In [26]:
```
full_data.head(5)
full_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 783764 entries, 1 to 455502
Data columns (total 20 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   ip.id                 783764 non-null  int64  
 1   ip.flags.df           783764 non-null  float64
 2   ip.ttl                783764 non-null  float64
 3   ip.len                783764 non-null  float64
 4   ip.dsfield            783764 non-null  int64  
 5   tcp.srcport           783764 non-null  float64
 6   tcp.seq               783764 non-null  float64
 7   tcp.len               783764 non-null  float64
 8   tcp.hdr_len           783764 non-null  float64
 9   tcp.flags.fin         783764 non-null  float64
 10  tcp.flags.syn         783764 non-null  float64
 11  tcp.flags.reset       783764 non-null  float64
 12  tcp.flags.push        783764 non-null  float64
 13  tcp.flags.ack         783764 non-null  float64
 14  tcp.flags.urg         783764 non-null  float64
 15  tcp.flags.cwr         783764 non-null  float64
 16  tcp.window_size       783764 non-null  float64
 17  tcp.urgent_pointer    783764 non-null  float64
 18  tcp.options.mss_val   783764 non-null  float64
 19  label                 783764 non-null  object 
dtypes: float64(17), int64(2), object(1)
memory usage: 125.6+ MB
```

Drop duplicates records

In [27]:
```
full_data.drop_duplicates(inplace=True, ignore_index=True)
```

In [28]:
```
full_data['label'].value_counts()
```

Out[28]:
```
label
1    362150
0    315729
Name: count, dtype: int64
```

======

save preprocessed dataset into CSV file

In [29]:
```
full_data.to_csv("full_data_preproces_main.csv", index=False)
```

preparation of dataset

In [30]:
```
full_data = full_data.fillna(0)
X = full_data.drop(columns = ["label"])
y = full_data.label

print(X.shape, y.shape)
```

```
(677879, 19) (677879,)
```

In [31]:
```
X = X.astype(int)
X.head()
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 677879 entries, 0 to 677878
Data columns (total 19 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   ip.id                677879 non-null  int64
 1   ip.flags.df          677879 non-null  int64
 2   ip.ttl               677879 non-null  int64
 3   ip.len               677879 non-null  int64
 4   ip.dsfield           677879 non-null  int64
 5   tcp.srcport          677879 non-null  int64
 6   tcp.seq              677879 non-null  int64
 7   tcp.len              677879 non-null  int64
 8   tcp.hdr_len          677879 non-null  int64
 9   tcp.flags.fin        677879 non-null  int64
 10  tcp.flags.syn        677879 non-null  int64
 11  tcp.flags.reset      677879 non-null  int64
 12  tcp.flags.push       677879 non-null  int64
 13  tcp.flags.ack        677879 non-null  int64
 14  tcp.flags.urg        677879 non-null  int64
 15  tcp.flags.cwr        677879 non-null  int64
 16  tcp.window_size      677879 non-null  int64
 17  tcp.urgent_pointer   677879 non-null  int64
 18  tcp.options.mss_val  677879 non-null  int64
dtypes: int64(19)
memory usage: 98.3 MB
```

Grid Search for Machine Learning Algorithms

ML model generation

In [34]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.calibration import CalibratedClassifierCV

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import StratifiedKFold, GridSearchCV
from sklearn.metrics import make_scorer, f1_score, roc_auc_score, accuracy_score

algorithms = {
    "SVM" : (LinearSVC(random_state=17), {}),
    "KNN" : (KNeighborsClassifier(n_jobs=-1), {
        "n_neighbors" : [1, 3, 5]
    }),
     "MLP" : (MLPClassifier(random_state=17), {
        "hidden_layer_sizes" : (10, 10),
    }),
    "NB" : (GaussianNB(), {}),
    "XGB" : (XGBClassifier(random_state=17, n_jobs=-1), {}),
    "LR" : (LogisticRegression(random_state=17, n_jobs=-1), {}),

    "RF" : (RandomForestClassifier(random_state=17, n_jobs=-1), {
        "n_estimators" : [10, 15, 20],
        "criterion" : ("gini", "entropy"),
        "max_depth": [5, 10],
        "class_weight": (None, "balanced", "balanced_subsample")
    }),
    "DT" : (DecisionTreeClassifier(random_state=17), {
        "criterion": ("gini", "entropy"),
        "max_depth": [5, 10, 15],
        "class_weight": (None, "balanced")
    }),
}
```

Best parameters estimation by f1-score

In [35]:
```
# Train, Test
k_fold_cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=17)
# Validation
grid_search_k_fold = StratifiedKFold(n_splits=3, shuffle=True, random_state=17)
# Performance metric
# f1-score; it can be considered roc_auc score for binary classification (attack

performance_scores = {}
best_parameters = {}
# placeholder for algos and their scores
for algo in algorithms.keys():
    performance_scores[algo] = { 'actual': [], 'predicted': [] }


for algo, (model, def_params) in algorithms.items():
  print(algo)
  # inner loop runs k times eql to num of folds
  for train_fold, test_fold in k_fold_cv.split(X, y):
    # scale the train fold set
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X.iloc[train_fold])
    y_train = y.iloc[train_fold]

    # fit the parameter estimator
    estimator = GridSearchCV(model, def_params, cv=grid_search_k_fold, scoring=m
    estimator.fit(X_train, y_train)
    # save the best hyperparameters
    best_parameters[algo] = estimator.best_params_

    # scale the test fold set
    X_test = scaler.transform(X.iloc[test_fold])
    y_test = y.iloc[test_fold]

    # predict by the best candidate model
    y_pred = estimator.predict(X_test)

    # saving the y_test and y_pred for later evaluation
    # FOR ALL TEST FOLDS COMBINED
    performance_scores[algo]['actual'].extend(y_test)
    performance_scores[algo]['predicted'].extend(y_pred)
```

```
SVM
KNN
MLP
NB
XGB
LR
RF
DT
```

Grid search results of best model hyperparameters by f1-score

In [37]:
```
best_parameters
```

Out[37]:
```
{'SVM': {},
 'KNN': {'n_neighbors': 1},
 'MLP': {'hidden_layer_sizes': 10},
 'NB': {},
 'XGB': {},
 'LR': {},
 'RF': {'class_weight': 'balanced_subsample',
  'criterion': 'gini',
  'max_depth': 10,
  'n_estimators': 20},
 'DT': {'class_weight': None, 'criterion': 'entropy', 'max_depth': 15}}
```

ROC_AUC evaluation for best hyperparameter selection

best set of parameter estimation by roc_auc

In [38]:
```
algorithms2 = {
    "SVM" : (CalibratedClassifierCV(LinearSVC(random_state=17), n_jobs=-1), {}),
    "MLP" : (MLPClassifier(random_state=17), {
        "hidden_layer_sizes" : (10, 10),
    }),
    "KNN" : (KNeighborsClassifier(n_jobs=-1), {
        "n_neighbors" : [1, 3, 5]
    }),
    "XGB" : (XGBClassifier(random_state=17, n_jobs=-1), {}),
    "NB" : (GaussianNB(), {}),
    "LR" : (LogisticRegression(random_state=17, n_jobs=-1), {}),
    "RF" : (RandomForestClassifier(random_state=17, n_jobs=-1), {
        "n_estimators" : [10, 15, 20],
        "criterion" : ("gini", "entropy"),
        "max_depth": [5, 10],
        "class_weight": (None, "balanced", "balanced_subsample")
    }),
    "DT" : (DecisionTreeClassifier(random_state=17), {
        "criterion": ("gini", "entropy"),
        "max_depth": [5, 10, 15],
        "class_weight": (None, "balanced")
    }),
}
```

In [39]:
```
# Train, Test
k_fold_cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=17)
# Validation
grid_search_k_fold = StratifiedKFold(n_splits=3, shuffle=True, random_state=17)
# Performance metric
# roc_auc_score

performance_scores2 = {}
best_parameters2 = {}
for algo in algorithms2.keys():
    performance_scores2[algo] = {'actual': [], 'predicted': []}


for algo, (model, def_params) in algorithms2.items():
  print(algo)
  # inner loop runs k times eql to num of folds
  for train_fold, test_fold in k_fold_cv.split(X, y):

    # scale the train fold set
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X.iloc[train_fold])
    y_train = y.iloc[train_fold]

    # fit the parameter estimator
    estimator = GridSearchCV(model, def_params, cv=grid_search_k_fold, scoring=m
    estimator.fit(X_train, y_train)

    # save the best hyperparameters
    best_parameters2[algo] = estimator.best_params_

    # scale the test fold set
    X_test = scaler.transform(X.iloc[test_fold])
    y_test = y.iloc[test_fold]

    # predict by the best candidate model
    y_pred = estimator.predict_proba(X_test).transpose()[1]

    # saving y_test and y_pred for later evaluation
    performance_scores2[algo]['actual'].extend(y_test)
    performance_scores2[algo]['predicted'].extend(y_pred)
```

```
SVM
MLP
KNN
XGB
NB
LR
RF
DT
```

In [41]:
```
best_parameters2
```

Out[41]:
```
{'SVM': {},
 'MLP': {'hidden_layer_sizes': 10},
 'KNN': {'n_neighbors': 1},
 'XGB': {},
 'NB': {},
 'LR': {},
 'RF': {'class_weight': 'balanced_subsample',
  'criterion': 'gini',
  'max_depth': 10,
  'n_estimators': 20},
 'DT': {'class_weight': None, 'criterion': 'entropy', 'max_depth': 15}}
```

Evaluation metric scores of the best candidate model for each Algorithm on all TEST FOLDs combined

classification metrics scores for best set of parameters (candidate model) on ALL TEST FOLDs combined

In [ ]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_sc

metrics = [accuracy_score, precision_score, recall_score, f1_score,roc_auc_score
score_names = ['Accuracy', 'Precision', "Recall", 'F1', 'ROC']
scores = {}
for name in score_names:
    scores[name] = {}

# calculate the metrics scores
for i in range(len(metrics)):
    temp = {}
    for algo in algorithms.keys():
        if metrics[i] is metrics[-1]: # include the roc scores
            temp.update({algo:metrics[i](performance_scores2[algo]['actual'], pe
        else: # include rest of the scores
            temp.update({algo:metrics[i](performance_scores[algo]['actual'], per
    scores[score_names[i]] = dict(sorted(temp.items(), key=lambda item: item[1],
    del temp # release memory
```

In [254…
```
for key, value in scores.items():
    print(key)
    for k, v in value.items():
        print(k, v)
    print("\n")
```

```
Accuracy
DT 0.9999365668504261
XGB 0.9998731337008522
KNN 0.9991591419707647
RF 0.9989363883524935
MLP 0.9987696919361715
LR 0.9084556388381997
SVM 0.9016668166442684
NB 0.6913977273230179


Precision
DT 0.9998950806636424
XGB 0.9997984594572209
RF 0.9996074235650917
KNN 0.9989072003355668
MLP 0.9987135884808198
LR 0.8835125906084182
SVM 0.8668393113414143
NB 0.6338608243001745


Recall
DT 0.9999861935662019
NB 0.9999668645588844
XGB 0.9999641032721248
KNN 0.9995195361038244
MLP 0.9989838464724562
RF 0.9984012149661743
SVM 0.9640287173823001
LR 0.9544912329145382


F1
DT 0.9999406350394087
XGB 0.9998812745043901
KNN 0.9992132744071264
RF 0.9990039551683122
MLP 0.998848699195746
LR 0.9176314119836367
SVM 0.9128544235616496
NB 0.7758955554055776


ROC
XGB 0.9999988265040711
RF 0.9999860555451553
DT 0.9999408173859827
MLP 0.9999251679210259
KNN 0.9991326479584143
LR 0.9696534960046947
SVM 0.9617430380478496
NB 0.924145986912221
```

In [226…

```
for i in range(len(score_names)):

    print(score_names[i])
    score_df = pd.DataFrame(data=scores[score_names[i]], columns=scores[score_na
    score_df.to_csv(f"scores/{score_names[i]}_scores.csv", index=True)
```

```
Accuracy
Precision
Recall
F1
ROC
```

In [216…

```
score_df
```

Out[216]:

	XGB	RF	DT	MLP	KNN	LR	SVM	NB
ROC	0.999999	0.999986	0.999941	0.999925	0.999133	0.969653	0.961743	0.924146

In [ ]:

plotting the ROC/AUC curve

In [265…

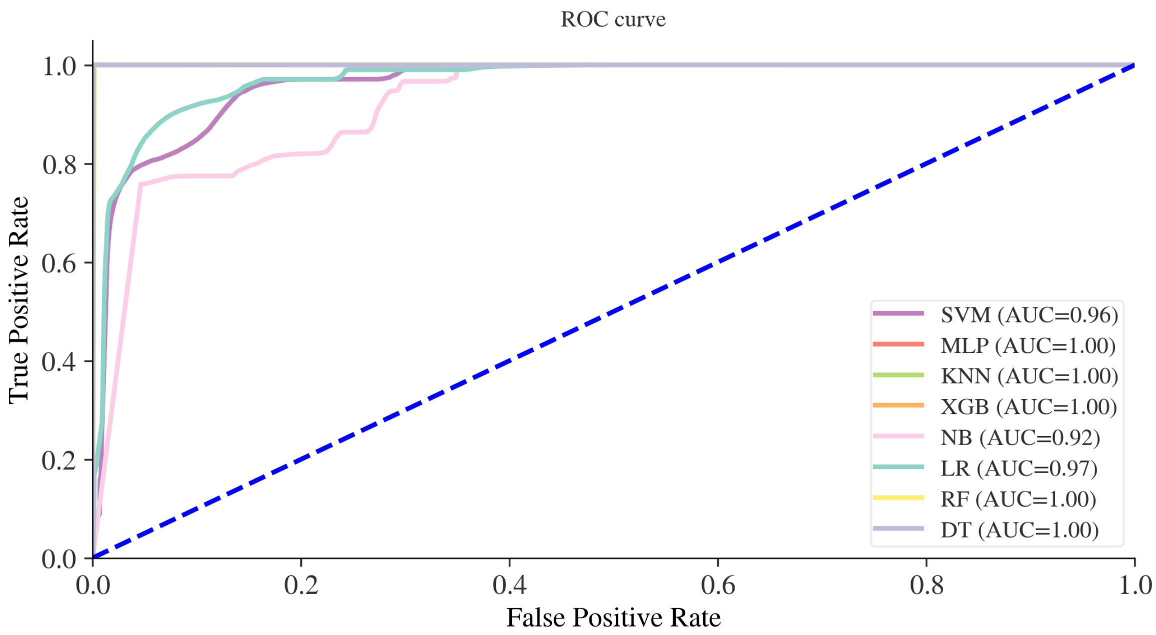
```
import os
from sklearn.metrics import auc

plt.figure(figsize=(8,4))

for algo, score in performance_scores2.items():
    fpr, tpr, threshold = roc_curve(score['actual'], score['predicted'])
    auc_score = auc(fpr,tpr)
    plt.plot(fpr, tpr, label="{} (AUC={:.2f})".format(algo, auc_score))


plt.plot([0,1], [0,1], color='blue', linestyle='--', linewidth=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC curve', fontsize=10, loc='center')
plt.legend(loc="lower right")

plt.savefig('figures/roc_curve_models.jpg', dpi=300, bbox_inches="tight")
```



ploting the scores of evaluation metrices

In [236…

```
def barplot( classifiers, scores, title, xlabel, ylabel):
    # Create a bar graph
    plt.figure(figsize=(12, 6))  # Set the size of the figure
    bars = plt.bar(classifiers, scores, color=['#1f77b4', '#ff7f0e', '#2ca02c',

    # Adding title and labels
    plt.title(title, fontsize=16)
    plt.xlabel(xlabel, fontsize=14)
    plt.ylabel(ylabel, fontsize=14)
    plt.ylim(0, 1)  # Set the y-axis range from 0 to 1

    # Adding the data labels on top of the bars
    for bar in bars:
        yval = bar.get_height()
        label_pos = yval - yval/10
        plt.text(bar.get_x() + bar.get_width()/2, label_pos, round(yval, 2), va=

    # Improve layout and show the plot
    plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better reada
    # plt.tight_layout()
    plt.grid(axis='y', linestyle='--', alpha=0.9)  # Add a grid for y-axis
    plt.savefig('figures/'+ylabel, dpi=300, bbox_inches="tight")
    plt.show()
```

accuracy scores of classifiers

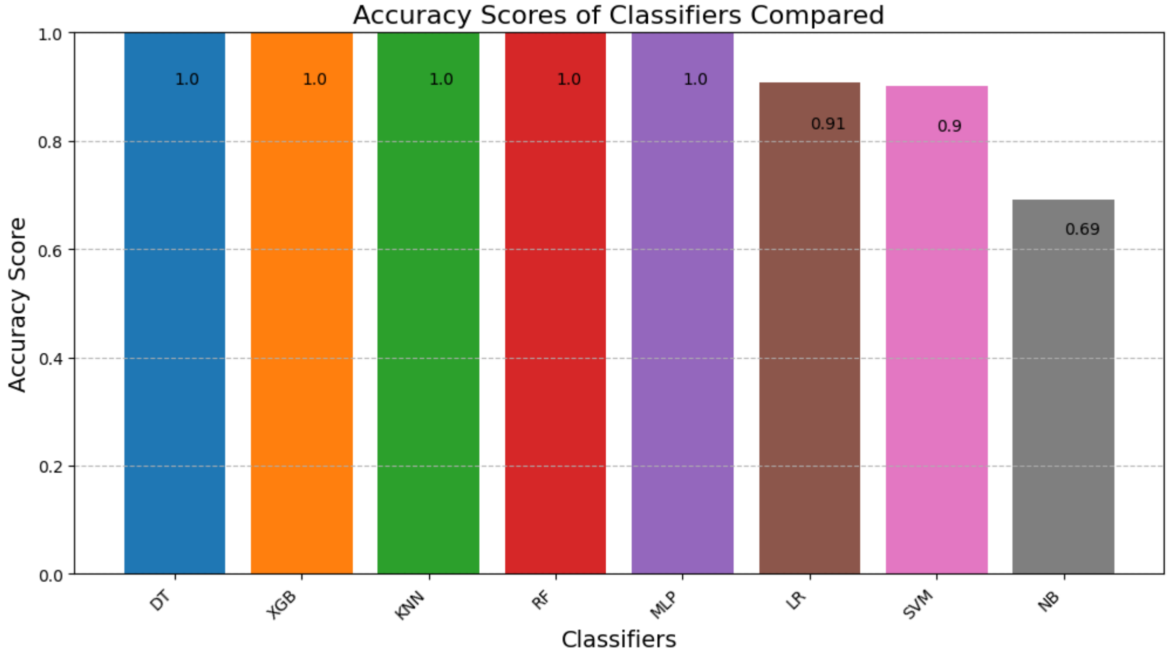
In [229…

```
accuracy_df = pd.read_csv('scores/Accuracy_scores.csv', index_col=0 )
accuracy_df
```

Out[229]:

	DT	XGB	KNN	RF	MLP	LR	SVM	NB
Accuracy	0.999937	0.999873	0.999159	0.998936	0.99877	0.908456	0.901667	0.691398

In [245…
```
barplot(classifiers=accuracy_df.columns, scores=accuracy_df.iloc[0], title="Accu
        xlabel="Classifiers", ylabel='Accuracy Score')
```



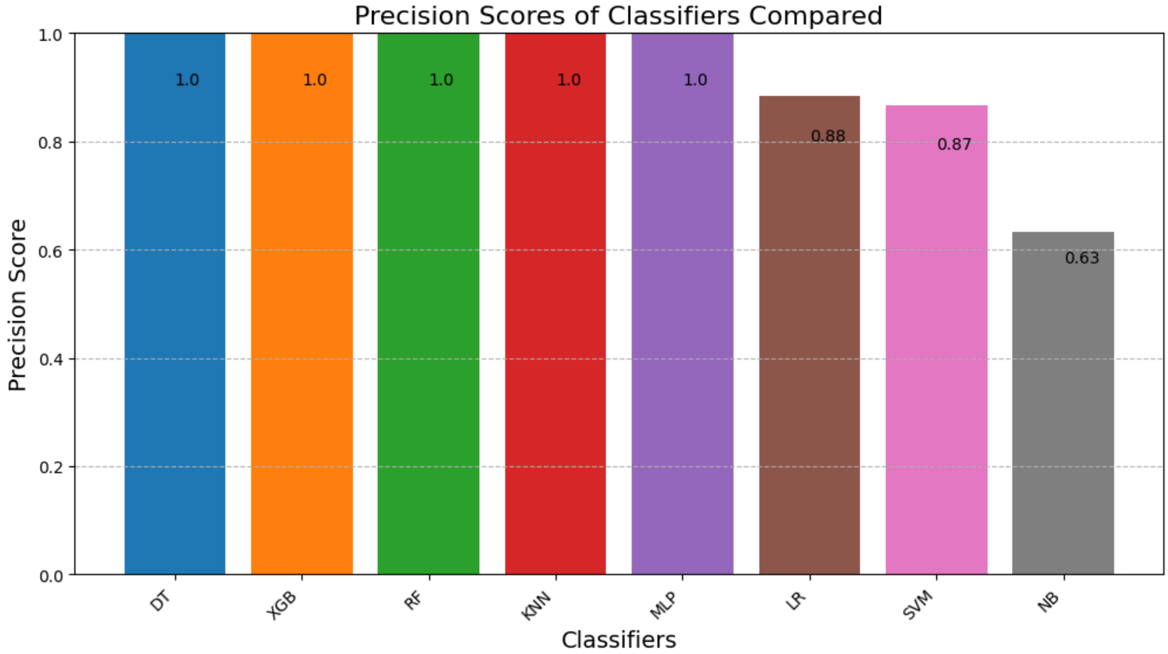
precision scores of classifiers

In [230…
```
precision_df = pd.read_csv('scores/Precision_scores.csv', index_col=0 )
precision_df
```

Out[230]:

	DT	XGB	RF	KNN	MLP	LR	SVM	NE
Precision	0.999895	0.999798	0.999607	0.998907	0.998714	0.883513	0.866839	0.63386

In [246…
```
barplot(classifiers=precision_df.columns, scores=precision_df.iloc[0], title="Pr
        xlabel="Classifiers", ylabel='Precision Score')
```



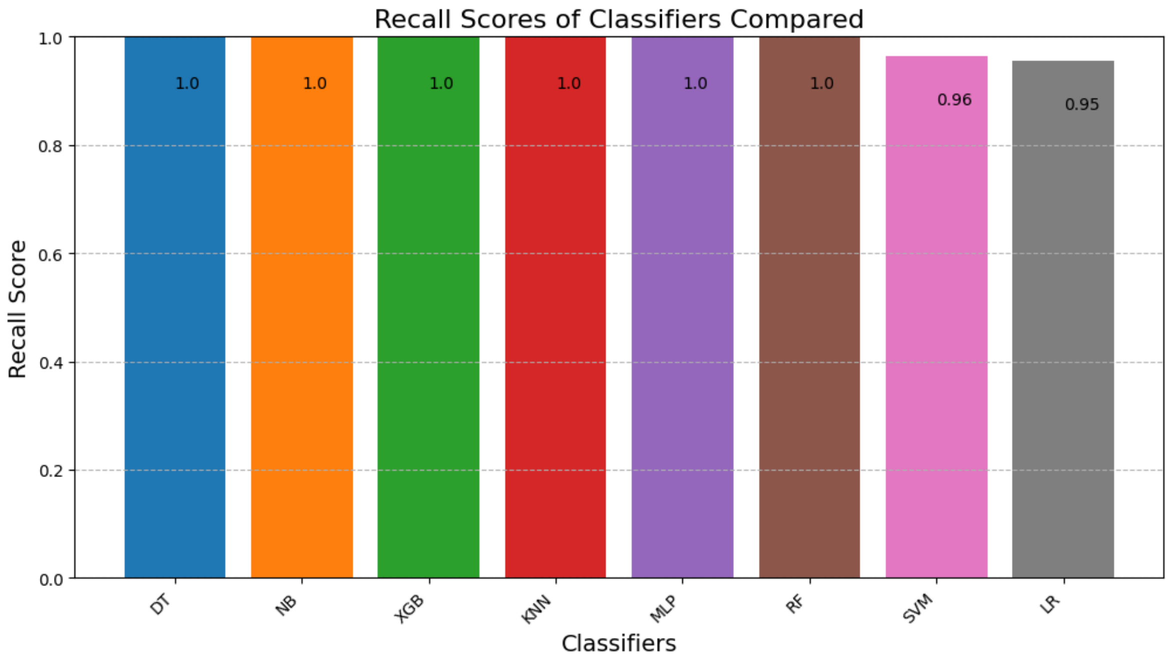
recall scores of classifiers

In [233…
```
recall_df = pd.read_csv('scores/Recall_scores.csv', index_col=0 )
recall_df
```

Out[233]:

	DT	NB	XGB	KNN	MLP	RF	SVM	LR
Recall	0.999986	0.999967	0.999964	0.99952	0.998984	0.998401	0.964029	0.954491

In [247…
```
barplot(classifiers=recall_df.columns, scores=recall_df.iloc[0], title="Recall S
        xlabel="Classifiers", ylabel='Recall Score')
```



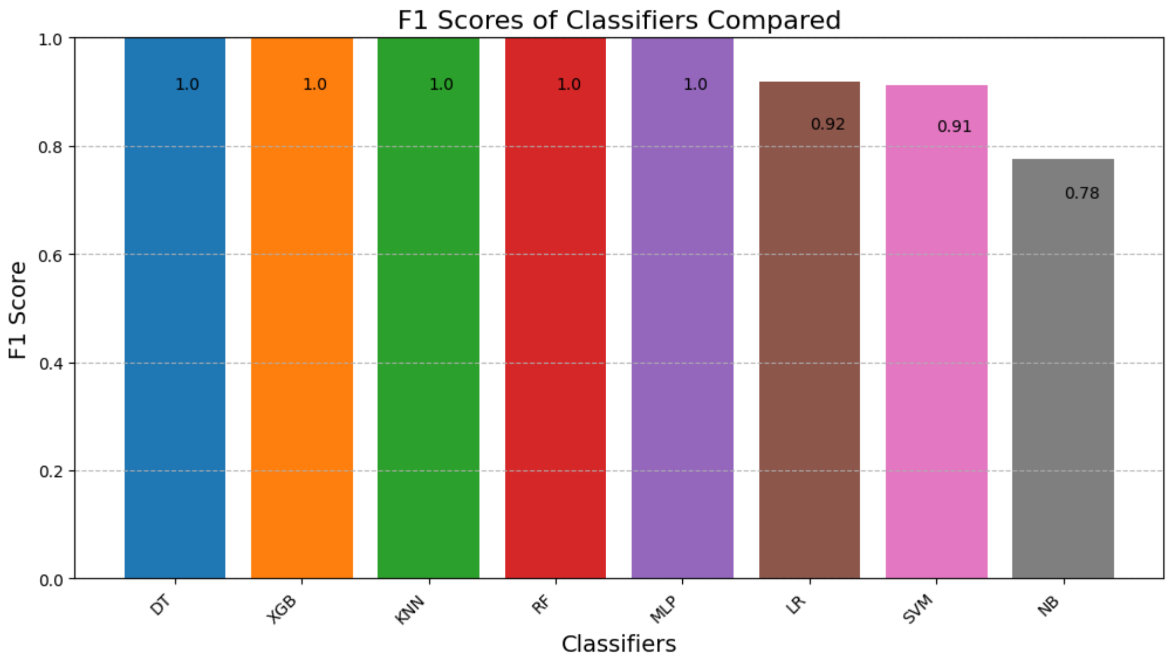
recall scores of classifier

In [234…
```
f1_df = pd.read_csv('scores/F1_scores.csv', index_col=0)
f1_df
```

Out[234]:

	DT	XGB	KNN	RF	MLP	LR	SVM	NB
F1	0.999941	0.999881	0.999213	0.999004	0.998849	0.917631	0.912854	0.775896

In [248…
```
barplot(classifiers=f1_df.columns, scores=f1_df.iloc[0], title="F1 Scores of Cla
        xlabel="Classifiers", ylabel='F1 Score')
```



roc scores for classifiers

In [235…

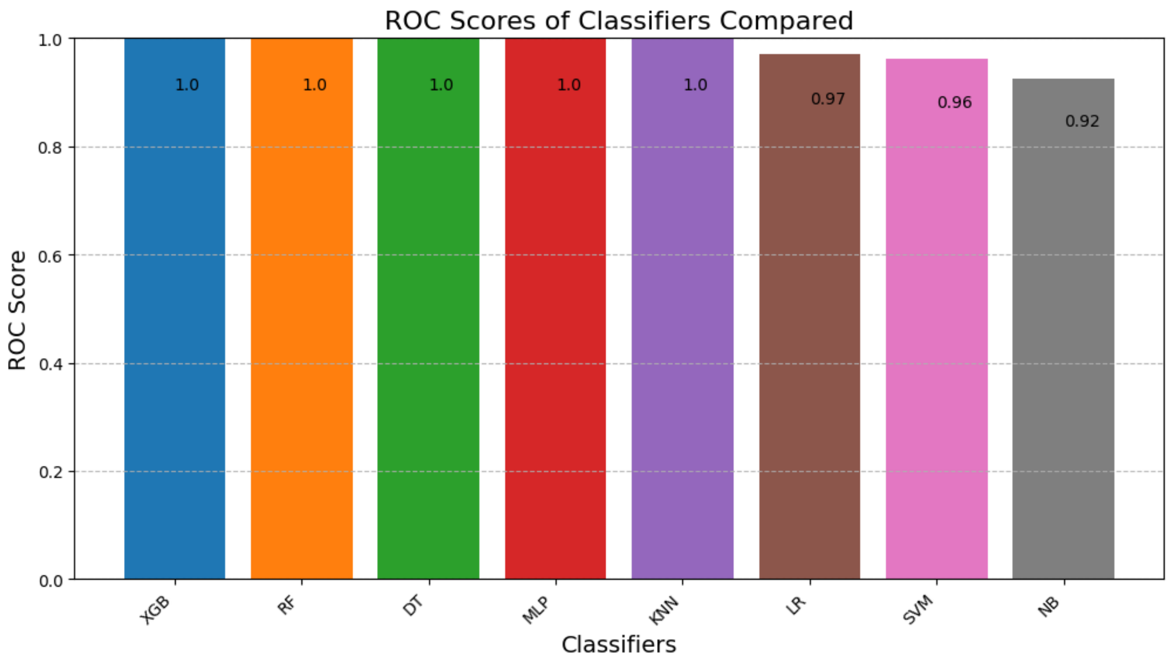
```
roc_df = pd.read_csv('scores/ROC_scores.csv', index_col=0)
roc_df
```

Out[235]:

	XGB	RF	DT	MLP	KNN	LR	SVM	NB
ROC	0.999999	0.999986	0.999941	0.999925	0.999133	0.969653	0.961743	0.924146

In [249…

```
barplot(classifiers=roc_df.columns, scores=roc_df.iloc[0], title="ROC Scores of
        xlabel="Classifiers", ylabel='ROC Score')
```



In [ ]: