```
### Internet Firewall Data
```

Additional Information

There are 12 features in total. Action feature is used as a class. There are 4 classes in total. These are allow, action, drop and reset-both classes.

```
###!pip install keras-tuner
```

```
###! unzip /content/internet+firewall+data.zip
```

```
###! pip install tensorflow
###! pip install bayesian-optimization
```

```
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn import preprocessing
import matplotlib.pyplot as plt
tf.random.set_seed(123)
np.random.seed(123)

# Import packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from keras.models import Sequential
from keras.layers import Dense, BatchNormalization, Dropout
from tensorflow.keras.optimizers import Adam, SGD, RMSprop, Adadelta, Adagrad, Adamax, Nadam, Ftrl
from keras.callbacks import EarlyStopping, ModelCheckpoint
###from keras.wrappers.scikit_learn import KerasClassifier
from math import floor
from sklearn.metrics import make_scorer, accuracy_score
from bayes_opt import BayesianOptimization
from sklearn.model_selection import StratifiedKFold
from keras.layers import LeakyReLU
LeakyReLU = LeakyReLU(alpha=0.1)
import warnings
warnings.filterwarnings('ignore')
pd.set_option("display.max_columns", None)
```

```
log_data = pd.read_csv("/content/log2.csv")
```

```
log_data.columns
```

```
Index(['Source Port', 'Destination Port', 'NAT Source Port',
       'NAT Destination Port', 'Action', 'Bytes', 'Bytes Sent',
       'Bytes Received', 'Packets', 'Elapsed Time (sec)', 'pkts_sent',
       'pkts_received'],
      dtype='object')
```

```
log_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 65532 entries, 0 to 65531
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   Source Port           65532 non-null  int64 
 1   Destination Port      65532 non-null  int64 
 2   NAT Source Port       65532 non-null  int64 
 3   NAT Destination Port  65532 non-null  int64 
 4   Action                65532 non-null  object
 5   Bytes                 65532 non-null  int64 
 6   Bytes Sent            65532 non-null  int64 
 7   Bytes Received        65532 non-null  int64 
 8   Packets               65532 non-null  int64 
 9   Elapsed Time (sec)    65532 non-null  int64 
 10  pkts_sent             65532 non-null  int64 
 11  pkts_received         65532 non-null  int64 
dtypes: int64(11), object(1)
memory usage: 6.0+ MB
```

```
from sklearn.model_selection import train_test_split
```

```
training_data, testing_data = train_test_split(log_data, test_size = 0.3, random_state = 0)
```

```
print(training_data.shape, testing_data.shape)
```

```
(45872, 12) (19660, 12)
```

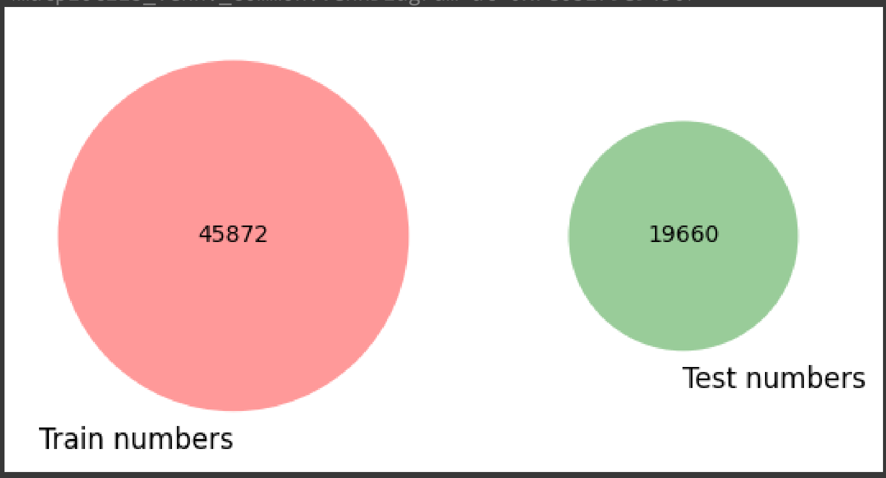
```
training_data['ID'] = training_data.index
testing_data['ID'] = testing_data.index
```

```
###! pip install matplotlib_venn
from matplotlib_venn import venn2, venn2_circles, venn2_unweighted
from matplotlib_venn import venn3, venn3_circles
```

```
set_numbers_train = set(training_data[['ID']].drop_duplicates().sort_values(by = 'ID')['ID'].tolist())
set_numbers_test = set(testing_data[['ID']].drop_duplicates().sort_values(by = 'ID')['ID'].tolist())
venn2((set_numbers_train, set_numbers_test), set_labels = ('Train numbers', 'Test numbers'))
```

```
venn2((set_numbers_train, set_numbers_test), set_labels = ('Train numbers', 'Test numbers'))
```

```
<matplotlib_venn._common.VennDiagram at 0x7e6b179e9450>
```



```
training_data.columns
```

```
Index(['Source Port', 'Destination Port', 'NAT Source Port',
       'NAT Destination Port', 'Action', 'Bytes', 'Bytes Sent',
       'Bytes Received', 'Packets', 'Elapsed Time (sec)', 'pkts_sent',
       'pkts_received', 'ID'],
      dtype='object')
```

```
num_var = [feature for feature in training_data.columns if training_data[feature].dtypes != 'O']
discrete_var = [feature for feature in num_var if len(training_data[feature].unique()) <= 25]
cont_var = [feature for feature in num_var if feature not in discrete_var]
categ_var = [feature for feature in training_data.columns if feature not in num_var]
```

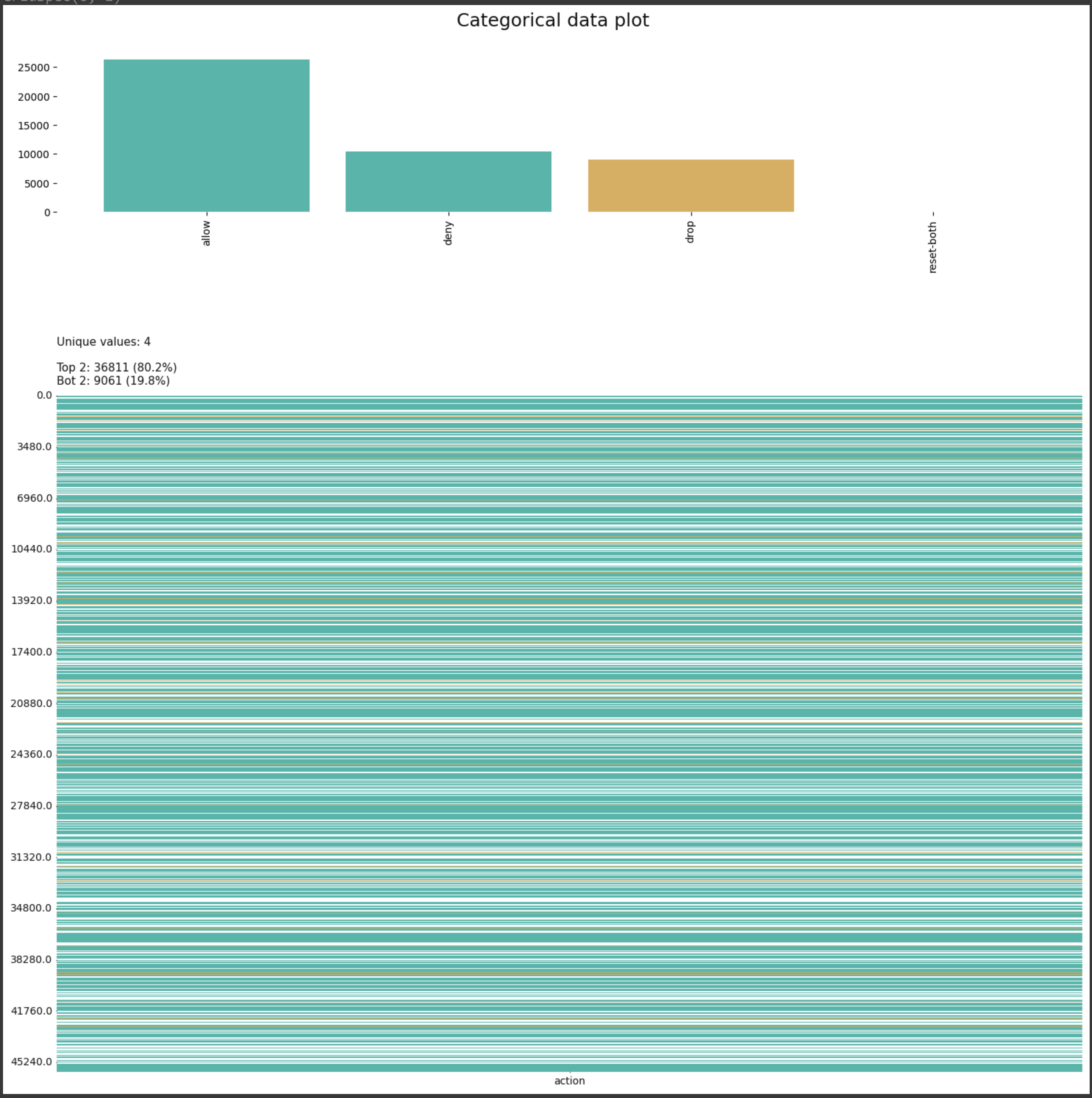
```
###! pip install klib
####!pip install keras-tuner
```

```
import klib
```

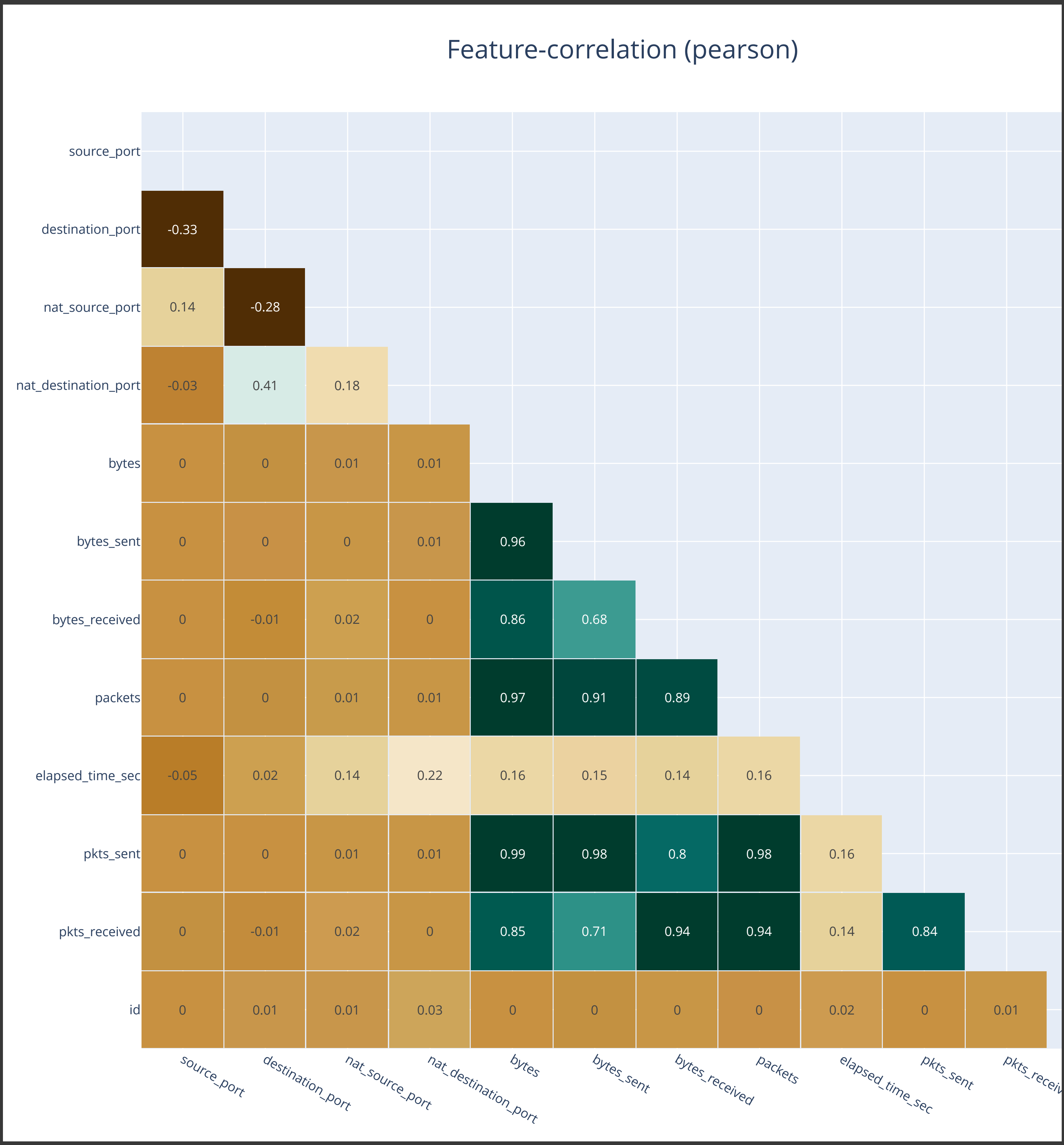
```
training_data = klib.clean_column_names(training_data)
testing_data = klib.clean_column_names(testing_data)
```

```
klib.cat_plot(training_data)
```

```
GridSpec(6, 1)
```

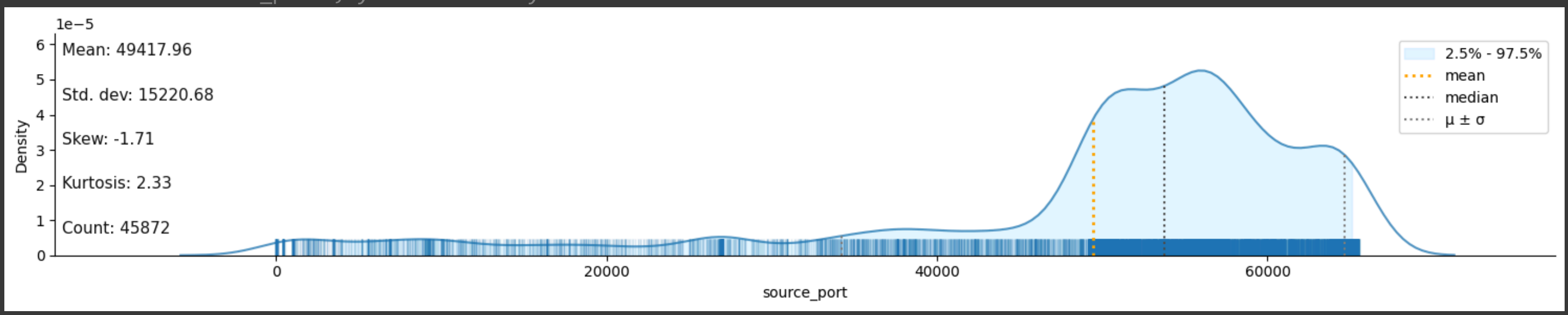


```
klib.corr_interactive_plot(training_data)
```



```
klib.dist_plot(training_data)
```

```
Large dataset detected, using 10000 random samples for the plots. Summary statistics are still based on the entire dataset.
<Axes: xlabel='source_port', ylabel='Density'>
```



```
klib.missingval_plot(training_data)
```

```
No missing values found in the dataset.
```

```
klib.corr_mat(training_data)
```

	source_port	destination_port	nat_source_port	nat_destination_port	bytes	bytes_sent	bytes_received	packe
source_port	1.00	-0.33	0.14	-0.03	-0.00	-0.00	0.00	-0
destination_port	-0.33	1.00	-0.28	0.41	-0.00	0.00	-0.01	-0
nat_source_port	0.14	-0.28	1.00	0.18	0.01	0.00	0.02	0
nat_destination_port	-0.03	0.41	0.18	1.00	0.01	0.01	-0.00	0
bytes	-0.00	-0.00	0.01	0.01	1.00	0.96	0.86	0
bytes_sent	-0.00	0.00	0.00	0.01	0.96	1.00	0.68	0
bytes_received	0.00	-0.01	0.02	-0.00	0.86	0.68	1.00	0
packets	-0.00	-0.00	0.01	0.01	0.97	0.91	0.89	1
elapsed_time_sec	-0.05	0.02	0.14	0.22	0.16	0.15	0.14	0
pkts_sent	-0.00	-0.00	0.01	0.01	0.99	0.98	0.80	0
pkts_received	-0.00	-0.01	0.02	0.00	0.85	0.71	0.94	0
id	-0.00	0.01	0.01	0.03	-0.00	-0.00	0.00	0

```
training_data.columns
```

```
     Index(['source_port', 'destination_port', 'nat_source_port',
            'nat_destination_port', 'action', 'bytes', 'bytes_sent',
            'bytes_received', 'packets', 'elapsed_time_sec', 'pkts_sent',
            'pkts_received', 'id'],
           dtype='object')
```

```
# Checking for outliers in the continuous variables
num_train_dataset = training_data[['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'action', 'bytes', 'bytes_sent',
       'bytes_received', 'packets', 'elapsed_time_sec', 'pkts_sent',
       'pkts_received', 'id']]
```

```
training_data['action'].value_counts()
```

```
     action
     allow         26311
     deny          10500
     drop           9021
     reset-both       40
     Name: count, dtype: int64
```

```
training_data['action'] = training_data['action'].astype('category').cat.codes
testing_data['action'] = testing_data['action'].astype('category').cat.codes
```

```
training_data['action'].value_counts()
```

```
     action
     0    26311
     1    10500
     2     9021
     3       40
     Name: count, dtype: int64
```

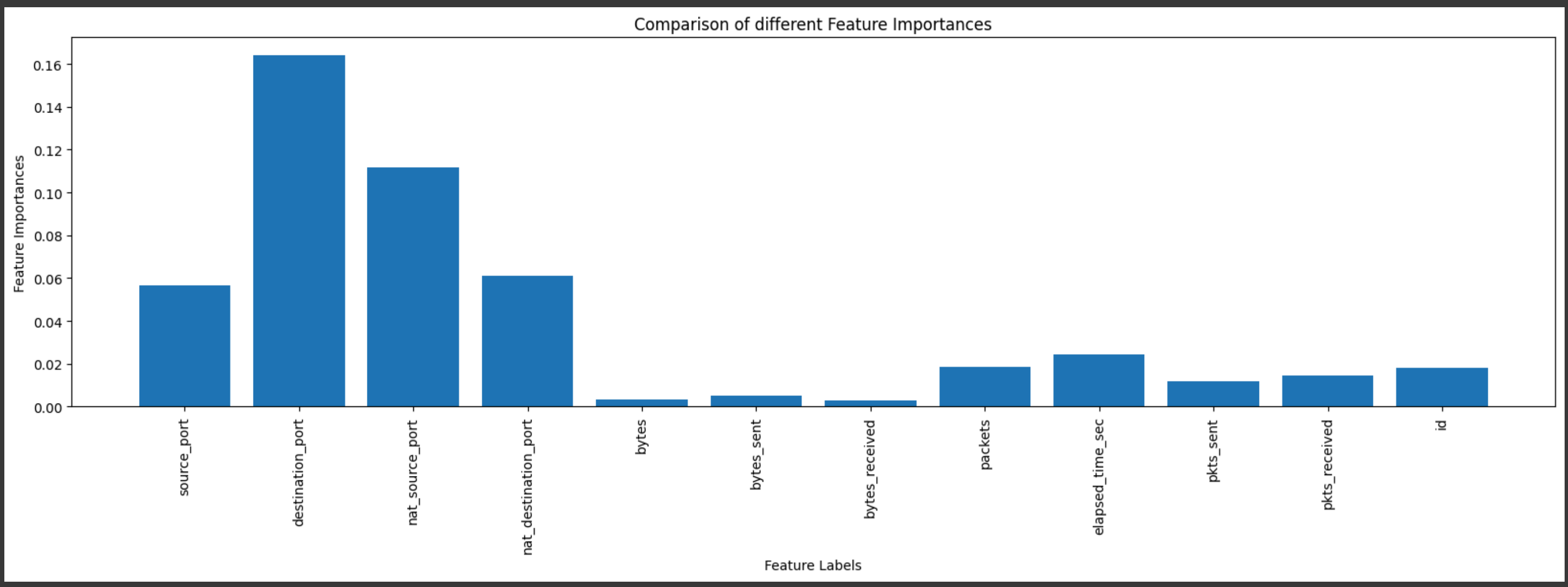
```
y_train = training_data['action']
x_train = training_data.drop('action', axis = 1)
y_test = testing_data['action']
x_test = testing_data.drop('action', axis = 1)
```

```
from sklearn.ensemble import ExtraTreesClassifier
extra_tree_forest = ExtraTreesClassifier(n_estimators = 5,
                                        criterion ='entropy', max_features = 2)
extra_tree_forest.fit(x_train, y_train)
feature_importance = extra_tree_forest.feature_importances_
feature_importance_normalized = np.std([tree.feature_importances_ for tree in
                                        extra_tree_forest.estimators_],
                                        axis = 0)
```

```
feature_importance_normalized
```

```
     array([0.05675952, 0.16426633, 0.11188091, 0.06129195, 0.00335718,
            0.00493371, 0.00305258, 0.0187216 , 0.0243437 , 0.01163417,
            0.01434409, 0.01811124])
```

```
plt.figure(figsize = [20,5])
plt.bar(x_train.columns, feature_importance_normalized)
plt.xlabel('Feature Labels')
plt.ylabel('Feature Importances')
plt.xticks(rotation = 90)
plt.title('Comparison of different Feature Importances')
plt.show()
```



```
print("The columns of the x_train :", x_train.columns)
print("The columns of the x_test :", x_test.columns)
```

```
     The columns of the x_train : Index(['source_port', 'destination_port', 'nat_source_port',
            'nat_destination_port', 'bytes', 'bytes_sent', 'bytes_received',
            'packets', 'elapsed_time_sec', 'pkts_sent', 'pkts_received', 'id'],
           dtype='object')
     The columns of the x_test : Index(['source_port', 'destination_port', 'nat_source_port',
            'nat_destination_port', 'bytes', 'bytes_sent', 'bytes_received',
            'packets', 'elapsed_time_sec', 'pkts_sent', 'pkts_received', 'id'],
           dtype='object')
```

```
x_train2 = x_train[['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'bytes', 'bytes_sent', 'bytes_received',
       'packets', 'elapsed_time_sec', 'pkts_sent', 'pkts_received']]
```

```
x_test2 = x_test[['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'bytes', 'bytes_sent', 'bytes_received',
       'packets', 'elapsed_time_sec', 'pkts_sent', 'pkts_received']]
```

```
print(x_train2.shape, x_test2.shape)
```

```
(45872, 11) (19660, 11)
```

```
y_train.value_counts()
```

```
action
0    26311
1    10500
2     9021
3       40
Name: count, dtype: int64
```

```
x_train2 = pd.DataFrame(x_train2)
x_test2 = pd.DataFrame(x_test2)
```

Pearson Correlation

```
x_train2.astype(float).corr()
```

	source_port	destination_port	nat_source_port	nat_destination_port	bytes	bytes_sent	bytes_received	p
source_port	1.000000	-0.332822	0.144624	-0.026874	-0.000384	-0.001174	0.001163	-0
destination_port	-0.332822	1.000000	-0.281346	0.410776	-0.003970	0.002086	-0.014347	-0
nat_source_port	0.144624	-0.281346	1.000000	0.176844	0.010345	0.002506	0.022666	0
nat_destination_port	-0.026874	0.410776	0.176844	1.000000	0.005874	0.009378	-0.001877	0
bytes	-0.000384	-0.003970	0.010345	0.005874	1.000000	0.961022	0.858692	0
bytes_sent	-0.001174	0.002086	0.002506	0.009378	0.961022	1.000000	0.683532	0
bytes_received	0.001163	-0.014347	0.022666	-0.001877	0.858692	0.683532	1.000000	0
packets	-0.002848	-0.004812	0.012151	0.006277	0.974205	0.907204	0.890350	1
elapsed_time_sec	-0.045490	0.023451	0.141599	0.219658	0.159429	0.148848	0.144997	0
pkts_sent	-0.002032	-0.001526	0.007036	0.007417	0.989239	0.975093	0.804198	0
pkts_received	-0.003874	-0.009608	0.019156	0.003822	0.853142	0.707939	0.940104	0

```
y_train = pd.DataFrame(y_train)
y_test = pd.DataFrame(y_test)
```

```
print(x_test2.columns, x_train2.columns)
```

```
Index(['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'bytes', 'bytes_sent', 'bytes_received',
       'packets', 'elapsed_time_sec', 'pkts_sent', 'pkts_received'],
      dtype='object') Index(['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'bytes', 'bytes_sent', 'bytes_received',
       'packets', 'elapsed_time_sec', 'pkts_sent', 'pkts_received'],
      dtype='object')
```

```
###!pip install pycaret
###! pip install jinja2
###! pip install markupsafe==2.0.1
```

```
import pycaret
from pycaret.classification import *
```

```
print(training_data.shape, testing_data.shape)
```

```
(45872, 13) (19660, 13)
```

```
training_data.columns
```

```
Index(['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'action', 'bytes', 'bytes_sent',
       'bytes_received', 'packets', 'elapsed_time_sec', 'pkts_sent',
       'pkts_received', 'id'],
      dtype='object')
```

```
model= setup(data= training_data, target= 'action')
```

	Description	Value
0	Session id	2131
1	Target	action
2	Target type	Multiclass
3	Original data shape	(45872, 13)
4	Transformed data shape	(45872, 13)
5	Transformed train set shape	(32110, 13)
6	Transformed test set shape	(13762, 13)
7	Numeric features	12
8	Preprocess	True
9	Imputation type	simple
10	Numeric imputation	mean
11	Categorical imputation	mode
12	Fold Generator	StratifiedKFold
13	Fold Number	10
14	CPU Jobs	-1
15	Use GPU	False
16	Log Experiment	False
17	Experiment Name	clf-default-name
18	USI	64b2

```
compare_models()
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
catboost	CatBoost Classifier	0.9986	0.9999	0.9986	0.9982	0.9984	0.9976	0.9976	32.1660
rf	Random Forest Classifier	0.9984	0.9997	0.9984	0.9978	0.9981	0.9972	0.9972	2.2140
et	Extra Trees Classifier	0.9983	0.9996	0.9983	0.9979	0.9981	0.9971	0.9971	1.3310
xgboost	Extreme Gradient Boosting	0.9983	0.9998	0.9983	0.9979	0.9981	0.9971	0.9971	1.6430
dt	Decision Tree Classifier	0.9980	0.9987	0.9980	0.9979	0.9979	0.9965	0.9965	0.1170
gbc	Gradient Boosting Classifier	0.9978	0.9992	0.9978	0.9976	0.9976	0.9961	0.9961	23.6360
ada	Ada Boost Classifier	0.9922	0.9982	0.9922	0.9917	0.9919	0.9867	0.9867	1.6200
lr	Logistic Regression	0.9879	0.9977	0.9879	0.9873	0.9875	0.9792	0.9793	6.5110
knn	K Neighbors Classifier	0.9858	0.9957	0.9858	0.9851	0.9854	0.9756	0.9756	0.5800
lightgbm	Light Gradient Boosting Machine	0.9687	0.9767	0.9687	0.9757	0.9691	0.9470	0.9487	4.6990
svm	SVM - Linear Kernel	0.9571	0.0000	0.9571	0.9474	0.9499	0.9257	0.9313	1.6580
ridge	Ridge Classifier	0.9161	0.0000	0.9161	0.9344	0.9188	0.8590	0.8650	0.0720
lda	Linear Discriminant Analysis	0.8814	0.9914	0.8814	0.9202	0.8885	0.8046	0.8178	0.0830
nb	Naive Bayes	0.6869	0.9971	0.6869	0.9750	0.7749	0.5833	0.6662	0.1220
dummy	Dummy Classifier	0.5736	0.5000	0.5736	0.3290	0.4181	0.0000	0.0000	0.0910
qda	Quadratic Discriminant Analysis	0.1999	0.0000	0.1999	0.0400	0.0667	0.0000	0.0000	0.0730

```
<catboost.core.CatBoostClassifier at 0x7e6abadd8fa0>
```

```
randomforest = create_model('rf')
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.9984	0.9998	0.9984	0.9978	0.9981	0.9973	0.9973
1	0.9988	0.9994	0.9988	0.9988	0.9987	0.9979	0.9979
2	0.9991	0.9998	0.9991	0.9989	0.9990	0.9984	0.9984
3	0.9978	0.9998	0.9978	0.9978	0.9977	0.9962	0.9962
4	0.9984	1.0000	0.9984	0.9984	0.9984	0.9973	0.9973
5	0.9978	0.9994	0.9978	0.9969	0.9974	0.9962	0.9962
6	0.9991	1.0000	0.9991	0.9981	0.9986	0.9984	0.9984
7	0.9984	0.9994	0.9984	0.9975	0.9980	0.9973	0.9973
8	0.9978	0.9998	0.9978	0.9969	0.9974	0.9962	0.9962
9	0.9981	0.9996	0.9981	0.9972	0.9977	0.9968	0.9968
Mean	0.9984	0.9997	0.9984	0.9978	0.9981	0.9972	0.9972
Std	0.0005	0.0002	0.0005	0.0007	0.0005	0.0008	0.0008

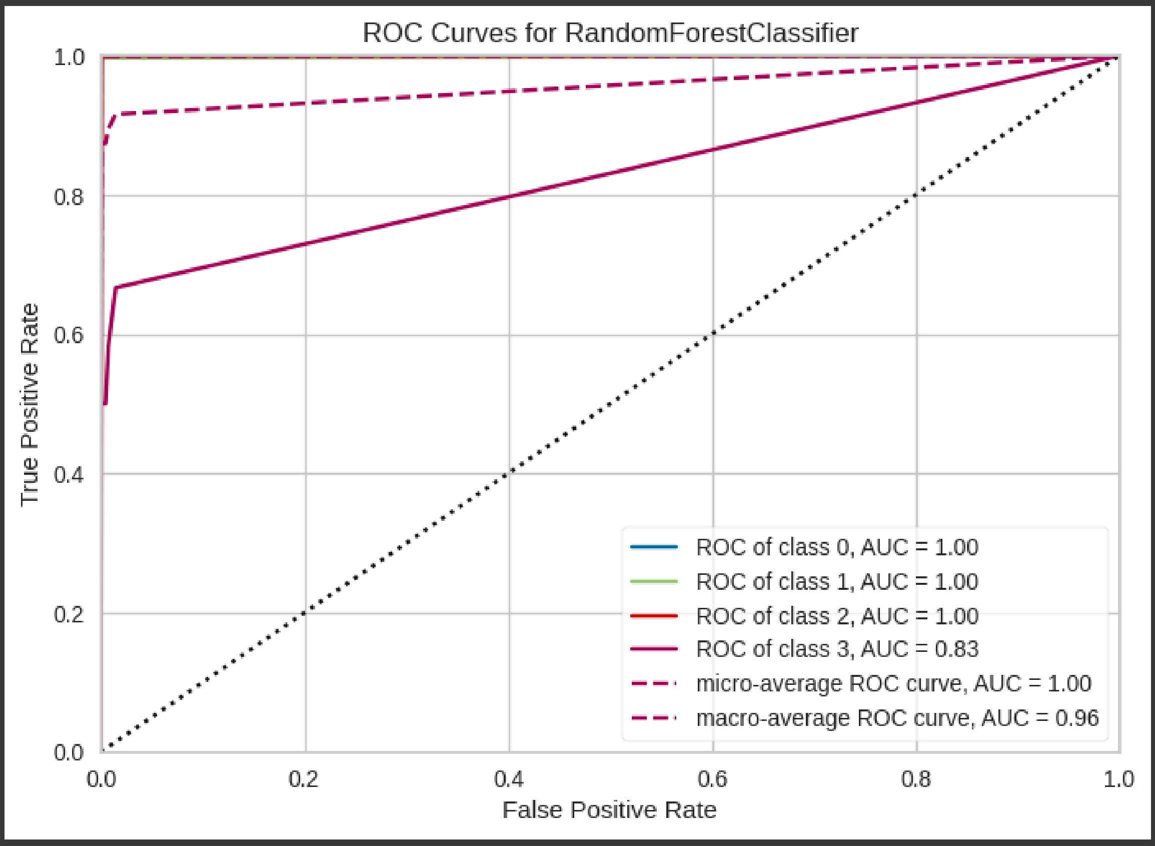
```
pred_holdout = predict_model(randomforest, data= testing_data)
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	Random Forest Classifier	0.9979	0.9994	0.9979	0.9979	0.9977	0.9963	0.9963

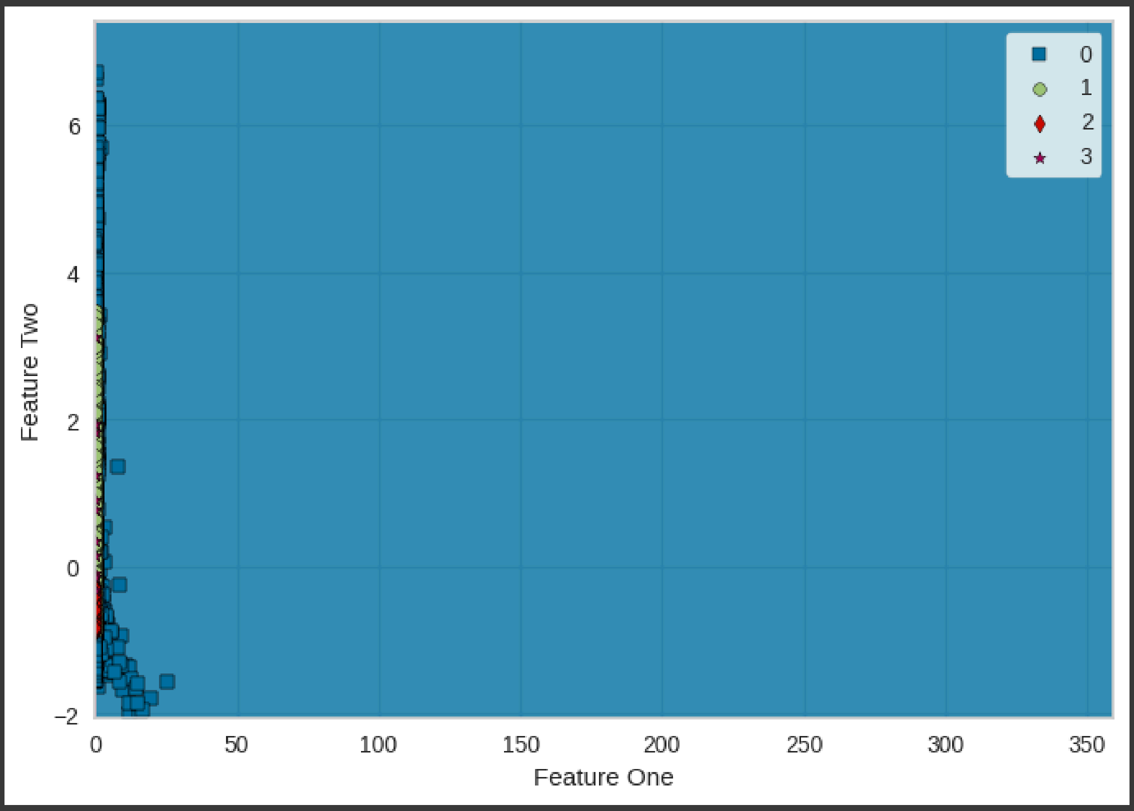
```
pred_holdout.columns
```

```
Index(['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'bytes', 'bytes_sent', 'bytes_received',
       'packets', 'elapsed_time_sec', 'pkts_sent', 'pkts_received', 'id',
       'action', 'prediction_label', 'prediction_score'],
      dtype='object')
```

```
# AUC-ROC plot
plot_model(randomforest, plot = 'auc')
```



```
# Decision Boundary
plot_model(randomforest, plot = 'boundary')
```



```
###! pip install shap
```

```
import shap
```

```
tune_randomforest = tune_model(randomforest)
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.9984	0.9998	0.9984	0.9978	0.9981	0.9973	0.9973
1	0.9981	0.9993	0.9981	0.9975	0.9978	0.9968	0.9968
2	0.9988	0.9993	0.9988	0.9978	0.9983	0.9979	0.9979
3	0.9981	0.9996	0.9981	0.9972	0.9977	0.9968	0.9968
4	0.9978	0.9991	0.9978	0.9969	0.9974	0.9962	0.9962
5	0.9978	0.9995	0.9978	0.9969	0.9974	0.9962	0.9962
6	0.9988	0.9997	0.9988	0.9978	0.9983	0.9979	0.9979
7	0.9981	0.9996	0.9981	0.9972	0.9977	0.9968	0.9968
8	0.9972	0.9995	0.9972	0.9963	0.9967	0.9952	0.9952
9	0.9988	0.9997	0.9988	0.9978	0.9983	0.9979	0.9979
Mean	0.9982	0.9995	0.9982	0.9973	0.9978	0.9969	0.9969
Std	0.0005	0.0002	0.0005	0.0005	0.0005	0.0008	0.0008

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits
Original model was better than the tuned model, hence it will be returned. NOTE: The display metrics are for the tuned model (no
print(tune_randomforest)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='sqrt',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_samples_leaf=1,
                       min_samples_split=2, min_weight_fraction_leaf=0.0,
                       monotonic_cst=None, n_estimators=100, n_jobs=-1,
                       oob_score=False, random_state=2131, verbose=0,
                       warm_start=False)
```

```
predict_model(tune_randomforest)
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
0	Random Forest Classifier	0.9981	0.9993	0.9981	0.9981	0.9979	0.9967	0.9967

	source_port	destination_port	nat_source_port	nat_destination_port	bytes	bytes_sent	bytes_received	packets	elapse
33873	58869	445	0	0	70	70	0	1	
59537	52027	445	0	0	66	66	0	1	
24581	55830	53	64690	53	183	94	89	2	
1724	65066	80	65066	80	874843	22526	852317	878	
46522	65378	53	28736	53	770	102	668	2	
...	...	...	...	...	...	...	...	...	
33470	13484	37965	0	0	62	62	0	1	
25312	24606	55783	0	0	72	72	0	1	
17978	61002	37965	0	0	145	145	0	1	
10142	49240	53	28241	53	198	101	97	2	
11889	64487	445	0	0	70	70	0	1	

13762 rows × 15 columns

```
final_randomforest = finalize_model(tune_randomforest)
print(final_randomforest)
```

```
Pipeline(memory=Memory(location=None),
         steps=[('numerical_imputer',
                 TransformerWrapper(exclude=None,
                                    include=['source_port', 'destination_port',
                                             'nat_source_port',
                                             'nat_destination_port', 'bytes',
                                             'bytes_sent', 'bytes_received',
                                             'packets', 'elapsed_time_sec',
                                             'pkts_sent', 'pkts_received',
                                             'id'],
                                    transformer=SimpleImputer(add_indicator=False,
                                                              copy=True,
                                                              fill_value=N...
                 RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                        class_weight=None, criterion='gini',
                                        max_depth=None, max_features='sqrt',
                                        max_leaf_nodes=None, max_samples=None,
                                        min_impurity_decrease=0.0,
                                        min_samples_leaf=1, min_samples_split=2,
                                        min_weight_fraction_leaf=0.0,
                                        monotonic_cst=None, n_estimators=100,
                                        n_jobs=-1, oob_score=False,
                                        random_state=2131, verbose=0,
                                        warm_start=False))],
         verbose=False)
```

```
print(training_data.shape, testing_data.shape)
```

```
(45872, 13) (19660, 13)
```

```
training_data['ID'] = training_data.index
testing_data['ID'] = testing_data.index
```

```
training_data.columns
```

```
Index(['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'action', 'bytes', 'bytes_sent',
       'bytes_received', 'packets', 'elapsed_time_sec', 'pkts_sent',
       'pkts_received', 'id', 'ID'],
      dtype='object')
```

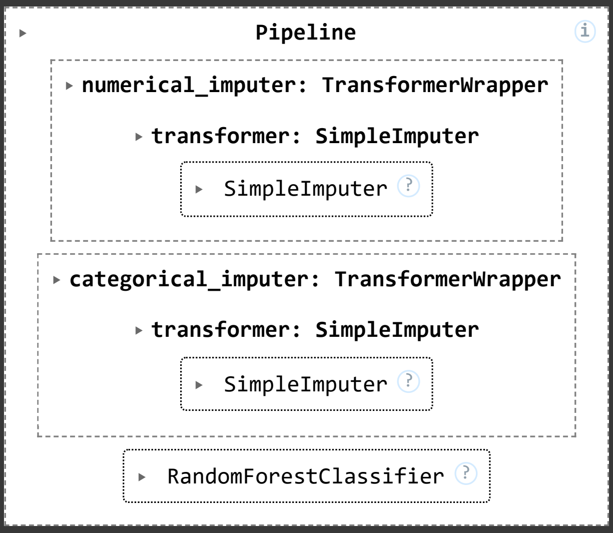
```
training_data2 = training_data[['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'action', 'bytes', 'bytes_sent',
       'bytes_received', 'packets', 'elapsed_time_sec', 'pkts_sent',
       'pkts_received']]
```

```
testing_data2 = testing_data[['source_port', 'destination_port', 'nat_source_port',
       'nat_destination_port', 'action', 'bytes', 'bytes_sent',
       'bytes_received', 'packets', 'elapsed_time_sec', 'pkts_sent',
       'pkts_received']]
```

```
X_train = training_data2.drop(columns= "action")
Y_train = training_data2["action"]

X_test = testing_data2.drop(columns= "action")
Y_test = testing_data2["action"]
```

```
final_randomforest.fit(X_train, Y_train)
```



Pipeline
numerical_imputer: TransformerWrapper
transformer: SimpleImputer
SimpleImputer
categorical_imputer: TransformerWrapper
transformer: SimpleImputer
SimpleImputer
RandomForestClassifier

```
Y_pred = final_randomforest.predict(X_test)
```

```
Y_pred = pd.DataFrame(Y_pred)
```

```
Y_pred.rename(columns = {0 : "pred_action"}, inplace = True)
```

```
Y_pred.shape
```

```
(19660, 1)
```

```
###! pip install pickle
```

```
# Save the trained model as a pickle string.
import pickle

saved_model = pickle.dump(final_randomforest, open('/content/final_randomforest_latest.pkl','wb'))
```