Import Libraries & Dataset

```
import time
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score

# Mount drive
from google.colab import drive
drive.mount('/content/drive')

# Path to your CSV file
csv_file_path = '/content/drive/My Drive/datasets/phishing_dataset_train.csv'

# Import Dataset
dataset = pd.read_csv(csv_file_path)

# Get Dataset shape (i.e. rows, cols)
print(dataset.shape)
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", forc
(700, 26)
```

Visualize Raw Dataset

```
# Visualize first 10 rows within dataset
dataset.head(10)
```

	domain_similarity	url_length	http_protocol	num_dot	num_slash	num
0	0.89	29	1	1	0	
1	0.88	28	1	1	0	
2	0.87	35	1	0	0	
3	0.49	64	1	1	3	
4	0.83	23	1	1	0	
5	0.88	20	1	0	0	
6	0.56	59	1	2	4	
7	0.32	63	1	0	4	
8	0.88	36	0	1	0	
9	0.87	27	1	1	0	

10 rows × 26 columns

View Dataset Features w/ Data Types

```
# View dataset feature names and their data types
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 700 entries, 0 to 699
Data columns (total 26 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   domain_similarity    700 non-null    float64
 1   url_length           700 non-null    int64
 2   http_protocol        700 non-null    int64
 3   num_dot              700 non-null    int64
 4   num_slash            700 non-null    int64
 5   num_double_slash     700 non-null    int64
 6   num_hyphen           700 non-null    int64
 7   num_underscore       700 non-null    int64
 8   num_equal            700 non-null    int64
 9   num_paranthesis      700 non-null    int64
 10  num_curly_bracket    700 non-null    int64
 11  num_square_bracket   700 non-null    int64
 12  num_less_and_greater 700 non-null    int64
 13  num_tilde            700 non-null    int64
 14  num_asterisk         700 non-null    int64
 15  num_plus             700 non-null    int64
 16  url_inc_at           700 non-null    int64
 17  url_inc_ip           700 non-null    int64
 18  response_history     700 non-null    int64
 19  redirect             700 non-null    int64
 20  num_a_href           700 non-null    int64
 21  num_input            700 non-null    int64
 22  num_button           700 non-null    int64
 23  num_link_href        700 non-null    int64
 24  num_iframe           700 non-null    int64
 25  class                700 non-null    int64
dtypes: float64(1), int64(25)
memory usage: 142.3 KB
```

Add New Column for Categorical Classification

```
# Consolidate all instances of the class labelled '1'
dataset['Classification'] = np.where(dataset['class']==1, 'Phishing', 'Non-Phishing')
dataset.head()
```

	domain_similarity	url_length	http_protocol	num_dot	num_slash	num
0	0.89	29	1	1	0	
1	0.88	28	1	1	0	
2	0.87	35	1	0	0	
3	0.49	64	1	1	3	
4	0.83	23	1	1	0	

5 rows × 27 columns

```
# Drop the Label feature since Class was added
dataset = dataset.drop(dataset.columns[-2],axis=1)
dataset.head()
```

	domain_similarity	url_length	http_protocol	num_dot	num_slash	num
0	0.89	29	1	1	0	
1	0.88	28	1	1	0	
2	0.87	35	1	0	0	
3	0.49	64	1	1	3	
4	0.83	23	1	1	0	

5 rows × 26 columns

Specify Feature Columns for Panda Dataframe Analysis

```
# Define features to be used by the classifier
features = pd.Index(['Domain Similarity', 'URL Length', 'HTTP Protocol',
                    'No. of Dot', 'No. of Slash', 'No. of Double Slash', 'No. of Hyphen',
                    'No. of Underscore', 'No. of Equal', 'No. of Parenthesis', 'No of Curly Bracket', 'No. of Square
                    'No. of Less Than and Greater Than', 'No. of Tilde', 'No. of Asterisk', 'No. of Plus', 'URL Incl
                    'Server Response History', 'Redirect', 'No. of <a> Tag', 'No. of <input> Tag', 'No. of <button>
                    'No. of <iframe> Tag'])
```

Conduct Dataset Cleaning

```
# Delete rows with null values
dataset.dropna(inplace=True)

# Remove duplicated rows (avoid overfitting)
dataset.drop_duplicates(inplace=True)

print(dataset.shape)
```

```
(641, 26)
```

Split Dataset into Training and Test Set

```
# With 'Classification' being the target variable, drop for X and add for y
X = dataset.drop('Classification', axis=1)
y = dataset['Classification']

# Split dataset into 85% training and 15% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15)
```

Perform Feature Scaling

```
# Using the StandardScaler from scikit-learn lib
# Create scaler obj
sc = StandardScaler()

# Compute the mean and std of the training data
X_train = sc.fit_transform(X_train)

# Compute the mean and std of the test data
X_test = sc.transform(X_test)
```

1. K-Nearest Neighbors Model Analysis

Training the K-NN model

```
# No. of neighbor cluster set to 5
# Distance metric set to minkowski (which is a combination of Manhattan and Euclidean)
# P=2 sets the minkowski to be more equivalent to Euclidean Distance
#knn = KNeighborsClassifier(n_neighbors= 5, metric = 'minkowski', p=2)
knn = KNeighborsClassifier()

# Train the K-NN classifier
knn.fit(X_train, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

Test K-NN Model Predictions

```
# Test the trained model using the test set
knn_start = time.time()
knn_pred = knn.predict(X_test)
knn_end = time.time()

# Calculate prediction time
knn_pred_time = knn_end - knn_start

print("KNN Prediction Time: ", knn_pred_time)
print("KNN Accuracy:",  accuracy_score(y_test, knn_pred))
print("KNN F1-score:", f1_score(y_test, knn_pred, pos_label = 'Phishing'))
```

```
KNN Prediction Time:  0.13606858253479004
KNN Accuracy: 0.979381443298969
KNN F1-score: 0.9807692307692307
```

2. Decision Tree Model Analysis

Training the DT model

```
# Criterion = Gini impurity
#dtree = DecisionTreeClassifier(criterion= 'gini', random_state=0)
dtree = DecisionTreeClassifier()

# Train the Decision Tree classifier
dtree.fit(X_train, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

Test Decision Tree Model Predictions

```
# Test the trained model using the test set
dt_start = time.time()
dtree_pred = dtree.predict(X_test)
dt_end = time.time()

# Calculate prediction time
dt_pred_time = dt_end - dt_start

print("DT Prediction Time: ", dt_pred_time)
print("DT Accuracy:",  accuracy_score(y_test, dtree_pred))
print("DT F1-score:", f1_score(y_test, dtree_pred, pos_label = 'Phishing'))
```

```
DT Prediction Time:  0.005805492401123047
DT Accuracy: 0.9896907216494846
DT F1-score: 0.9904761904761905
```

3. Random Forest Model Analysis

Training the RF model

```
# random forest model creation
rfc = RandomForestClassifier()

# Train the Random Forest classifier
rfc.fit(X_train,y_train)
```

```
▾ RandomForestClassifier
RandomForestClassifier()
```

Test RF Model Predictions

```
# Test the trained model using the test set
rf_start = time.time()
rf_pred = rfc.predict(X_test)
rf_end = time.time()

# Calculate prediction time
rf_pred_time = rf_end - rf_start

print("RF Prediction Time: ", rf_pred_time)
print("RF Accuracy:",  accuracy_score(y_test, rf_pred))
print("RF F1-score:", f1_score(y_test, rf_pred, pos_label = 'Phishing'))
```

```
RF Prediction Time:  0.01888728141784668
RF Accuracy: 1.0
RF F1-score: 1.0
```

4. Multilayer Perceptron Model Analysis

Training the MLP model

```
# Two hidden layers with 100 and 50 neurons
# ReLU Activation function
# Regularization term (L2)
# Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) optimization algorithm
#mlp = MLPClassifier(hidden_layer_sizes=(100,50), activation='relu', alpha=0.00001, max_iter=200, solver='lbfgs', ra
mlp = MLPClassifier()

# Train the Decision Tree classifier
mlp.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilay
  warnings.warn(
▾ MLPClassifier
MLPClassifier()
```

Test MLP Model Predictions

```
# Test the trained model using the test set
mlp_start = time.time()
mlp_pred = mlp.predict(X_test)
mlp_end = time.time()

# Calculate prediction time
mlp_pred_time = mlp_end - mlp_start

print("MLP Prediction Time: ", mlp_pred_time)
print("MLP Accuracy:",  accuracy_score(y_test, mlp_pred))
print("MLP F1-score:", f1_score(y_test, mlp_pred, pos_label = 'Phishing'))
```

```
MLP Prediction Time:  0.0059337615966796875
MLP Accuracy: 0.9587628865979382
MLP F1-score: 0.9607843137254902
```

Baseline Results Combined

```
from prettytable import PrettyTable

# Create a PrettyTable object
table = PrettyTable()

# Define column names
table.field_names = ["Model / Algorithm", "Prediction Time", "Accuracy", "F1-Score"]

# Add rows to the table
table.add_row(["KNN", knn_pred_time, accuracy_score(y_test, knn_pred), f1_score(y_test, knn_pred, pos_label = 'Phish
table.add_row(["DT", dt_pred_time, accuracy_score(y_test, dtree_pred), f1_score(y_test, dtree_pred, pos_label = 'Phi
table.add_row(["RF", rf_pred_time, accuracy_score(y_test, rf_pred), f1_score(y_test, rf_pred, pos_label = 'Phishing'
table.add_row(["MLP", mlp_pred_time, accuracy_score(y_test, mlp_pred), f1_score(y_test, mlp_pred, pos_label = 'Phish

print(table)
```

```
+-------------------+-----------------------+--------------------+--------------------+
| Model / Algorithm |    Prediction Time    |      Accuracy      |      F1-Score      |
+-------------------+-----------------------+--------------------+--------------------+
|        KNN        |  0.13606858253479004  | 0.979381443298969  | 0.9807692307692307 |
|         DT        |  0.005805492401123047 | 0.9896907216494846 | 0.9904761904761905 |
|         RF        |  0.01888728141784668  |        1.0         |        1.0         |
|        MLP        | 0.0059337615966796875 | 0.9587628865979382 | 0.9607843137254902 |
+-------------------+-----------------------+--------------------+--------------------+
```

Training the K-NN model w/ Param Fine-Tunning

```
# No. of neighbor cluster set to 5
# Distance metric set to minkowski (which is a combination of Manhattan and Euclidean)
# P=1 sets the minkowski to be more equivalent to Manhattan Distance
knn_model = KNeighborsClassifier(n_neighbors= 5, metric = 'minkowski', p=1)

# Train the K-NN classifier
knn_model.fit(X_train, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier(p=1)
```

```
# Test the trained model using the test set
knn_model_start = time.time()
knn_model_pred = knn_model.predict(X_test)
knn_model_end = time.time()

# Calculate prediction time
knn_model_pred_time = knn_model_end - knn_model_start

print("KNN w/ Fine-Tunning Prediction Time: ", knn_model_pred_time)
print("KNN w/ Fine-Tunning Accuracy:",  accuracy_score(y_test, knn_model_pred))
print("KNN w/ Fine-Tunning F1-score:", f1_score(y_test, knn_model_pred, pos_label = 'Phishing'))
```

```
KNN w/ Fine-Tunning Prediction Time:  0.016283512115478516
KNN w/ Fine-Tunning Accuracy: 0.979381443298969
KNN w/ Fine-Tunning F1-score: 0.9811320754716981
```

Training the DT model w/ Param Fine-Tunning

```
# Criterion = entropy
dt_model = DecisionTreeClassifier(criterion= 'entropy', random_state=42)

# Train the Decision Tree classifier
dt_model.fit(X_train, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=42)
```

```
# Test the trained model using the test set
dt_model_start = time.time()
dt_model_pred = dt_model.predict(X_test)
dt_model_end = time.time()

# Calculate prediction time
dt_model_pred_time = dt_model_end - dt_model_start

print("DT w/ Fine-Tunning Prediction Time: ", dt_model_pred_time)
print("DT w/ Fine-Tunning Accuracy:",  accuracy_score(y_test, dt_model_pred))
print("DT w/ Fine-Tunning F1-score:", f1_score(y_test, dt_model_pred, pos_label = 'Phishing'))
```

```
DT w/ Fine-Tunning Prediction Time:  0.002010345458984375
DT w/ Fine-Tunning Accuracy: 0.9896907216494846
DT w/ Fine-Tunning F1-score: 0.9904761904761905
```

Training the RF model w/ Param Fine-Tunning

```
from sklearn.model_selection import RandomizedSearchCV

# Create random grid
random_grid = {'bootstrap': [True, False], # Method of selecting samples for training each tree
               'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None], # Maximum number of levels in tree
               'max_features': ['auto', 'sqrt'], # Number of features to consider at every split
               'min_samples_leaf': [1, 2, 4], # Minimum number of samples required at each leaf node
               'min_samples_split': [2, 5, 10], # Minimum number of samples required to split a node
               'n_estimators': [130, 180, 230]} # Number of trees in random forest

# random forest model creation
rf = RandomForestClassifier()

# n_iter = 100 different sets of hyperparameters will be randomly selected and evaluated
# cv=3, each set of hyperparameters will be evaluated using 3-fold cross-validation
# verbosity: the higher the value, the more messages are printed
# n_jobs = number of jobs to run in parallel
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter = 100, cv = 3, verbose=2, r

# Train the Random Forest classifier
rf_random.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

```
# Test the trained model using the test set
rf_random_start = time.time()
rf_random_pred = rf_random.predict(X_test)
rf_random_end = time.time()

# Calculate prediction time
rf_random_pred_time = rf_random_end - rf_random_start

print("RF w/ Fine-Tunning Prediction Time: ", rf_random_pred_time)
print("RF w/ Fine-Tunning Accuracy:",  accuracy_score(y_test, rf_random_pred))
print("RF w/ Fine-Tunning F1-score:", f1_score(y_test, rf_random_pred, pos_label = 'Phishing'))
```

```
RF w/ Fine-Tunning Prediction Time:  0.017709016799926758
RF w/ Fine-Tunning Accuracy: 1.0
RF w/ Fine-Tunning F1-score: 1.0
```

Training the MLP model w/ Param Fine-Tunning

```
# Two hidden layers with 100 and 50 neurons
# ReLU Activation function
# Regularization term (L2)
# Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) optimization algorithm
mlp_model = MLPClassifier(hidden_layer_sizes=(100,50), activation='logistic', alpha=0.00001, max_iter=200, solver='a

# Train the Decision Tree classifier
mlp_model.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilay
  warnings.warn(
```

```
▾                           MLPClassifier
MLPClassifier(activation='logistic', alpha=1e-05, hidden_layer_sizes=(1
              random_state=42)
```

```
# Test the trained model using the test set
mlp_model_start = time.time()
mlp_model_pred = mlp_model.predict(X_test)
mlp_model_end = time.time()

# Calculate prediction time
mlp_model_pred_time = mlp_model_end - mlp_model_start

print("MLP Prediction Time: ", mlp_model_pred_time)
print("MLP Accuracy:",  accuracy_score(y_test, mlp_model_pred))
print("MLP F1-score:", f1_score(y_test, mlp_model_pred, pos_label = 'Phishing'))
```

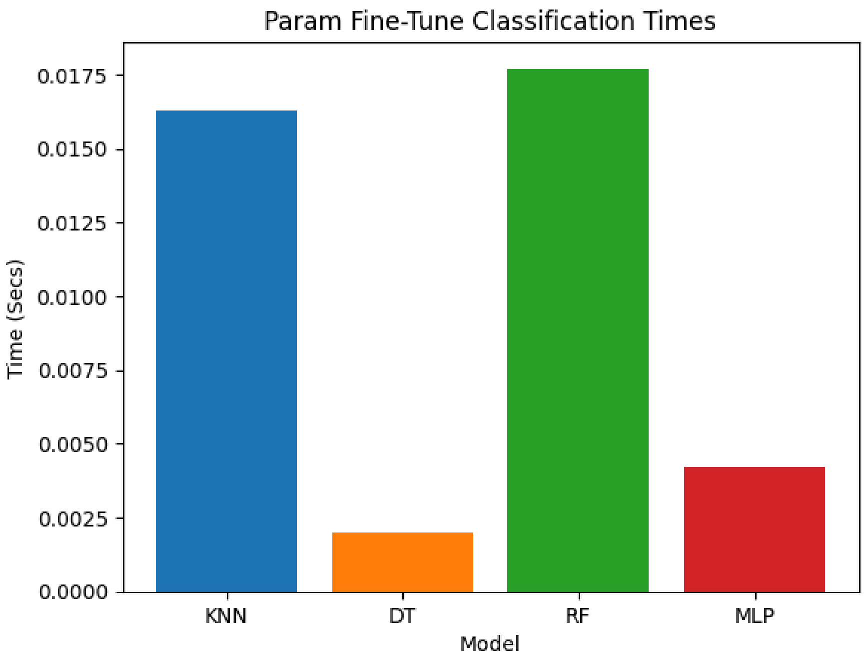
```
MLP Prediction Time:  0.004193544387817383
MLP Accuracy: 0.9484536082474226
MLP F1-score: 0.9514563106796117
```

Hyperparam Fine-tunning Models Results Combined

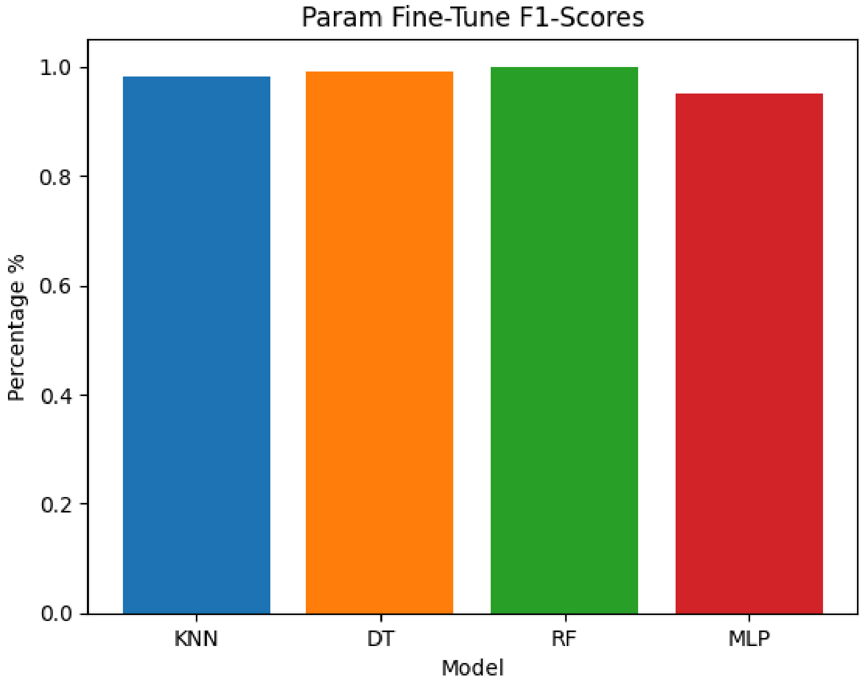
```
# Create a PrettyTable object
table = PrettyTable()

# Define column names
table.field_names = ["Model / Algorithm", "Prediction Time", "Accuracy", "F1-Score"]

# Add rows to the table
table.add_row(["KNN", knn_model_pred_time, accuracy_score(y_test, knn_model_pred), f1_score(y_test, knn_model_pred,
table.add_row(["DT", dt_model_pred_time, accuracy_score(y_test, dt_model_pred), f1_score(y_test, dt_model_pred, pos_
table.add_row(["RF", rf_random_pred_time, accuracy_score(y_test, rf_random_pred), f1_score(y_test, rf_random_pred, p
table.add_row(["MLP", mlp_model_pred_time, accuracy_score(y_test, mlp_model_pred), f1_score(y_test, mlp_model_pred,

print(table)
```

```
+-------------------+----------------------+--------------------+--------------------+
| Model / Algorithm |   Prediction Time    |      Accuracy      |      F1-Score      |
+-------------------+----------------------+--------------------+--------------------+
|        KNN        | 0.016283512115478516 | 0.979381443298969  | 0.9811320754716981 |
|         DT        | 0.002010345458984375 | 0.9896907216494846 | 0.9904761904761905 |
|         RF        | 0.017709016799926758 |        1.0         |        1.0         |
|        MLP        | 0.004193544387817383 | 0.9484536082474226 | 0.9514563106796117 |
+-------------------+----------------------+--------------------+--------------------+
```

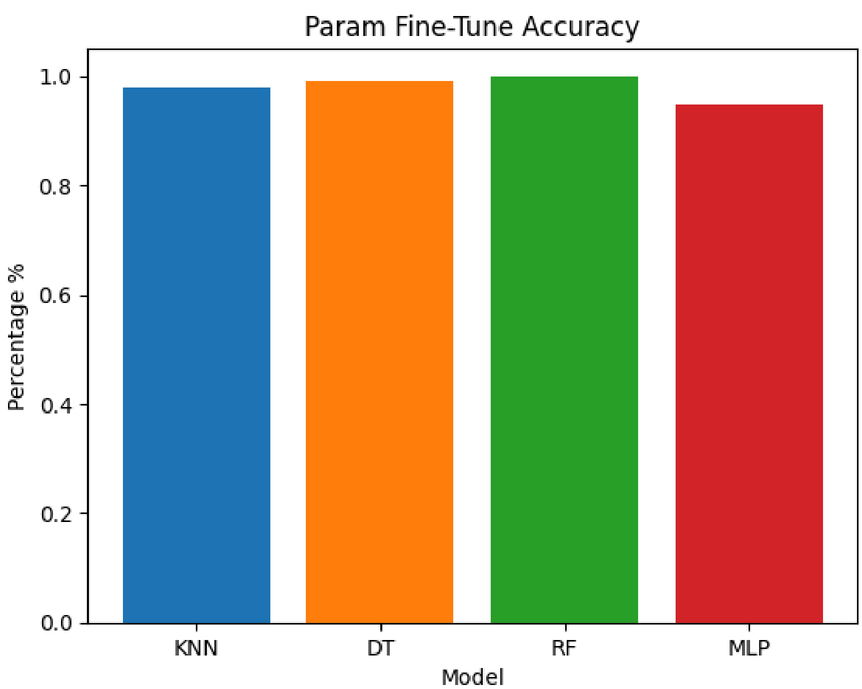
```
# Create bar chart using extracted values from table
plt.bar("KNN", knn_model_pred_time)
plt.bar("DT", dt_model_pred_time)
plt.bar("RF", rf_random_pred_time)
plt.bar("MLP", mlp_model_pred_time)

# Define chart labels
plt.title("Param Fine-Tune Classification Times")
plt.xlabel("Model")
plt.ylabel("Time (Secs)")

# Show plot
plt.show()
```




```
# Create bar chart using extracted values from table
plt.bar("KNN", f1_score(y_test, knn_model_pred, pos_label = 'Phishing'))
plt.bar("DT", f1_score(y_test, dt_model_pred, pos_label = 'Phishing'))
plt.bar("RF", f1_score(y_test, rf_random_pred, pos_label = 'Phishing'))
plt.bar("MLP", f1_score(y_test, mlp_model_pred, pos_label = 'Phishing'))

# Define chart labels
plt.title("Param Fine-Tune F1-Scores")
plt.xlabel("Model")
plt.ylabel("Percentage %")

# Show plot
plt.show()
```




```
# Create bar chart using extracted values from table
plt.bar("KNN", accuracy_score(y_test, knn_model_pred))
plt.bar("DT", accuracy_score(y_test, dt_model_pred))
plt.bar("RF", accuracy_score(y_test, rf_random_pred))
plt.bar("MLP", accuracy_score(y_test, mlp_model_pred))

# Define chart labels
plt.title("Param Fine-Tune Accuracy")
plt.xlabel("Model")
plt.ylabel("Percentage %")

# Show plot
plt.show()
```



Optimal Model Selection

Feature Selection using SelectKBest

```
# Feature Selection (K=10)
skb = SelectKBest(score_func=f_classif, k=10)

X_train_selected = skb.fit_transform(X_train, y_train)
X_test_selected = skb.transform(X_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:112: UserWarning: Fea
  warnings.warn("Features %s are constant." % constant_features_idx, UserWarning)
/usr/local/lib/python3.10/dist-packages/sklearn/feature_selection/_univariate_selection.py:113: RuntimeWarning:
  f = msb / msw
```

```
# Retrieve selected features
selected_features = skb.get_support(indices=True)

# Get feature names
selected_feature_names = X.columns[selected_features]

print("Selected feature names:", selected_feature_names)
```

```
Selected feature names: Index(['domain_similarity', 'url_length', 'http_protocol', 'num_slash',
       'num_hyphen', 'response_history', 'redirect', 'num_a_href',
       'num_link_href', 'num_iframe'],
      dtype='object')
```

Train & test the DT model (Optimal Selected Model)

```
# Optimal DT model creation
optimal_model = DecisionTreeClassifier(criterion= 'entropy', random_state=42)

# Train the Decision Tree classifier
optimal_model.fit(X_train_selected, y_train)
```

```
▾ DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=42)
```

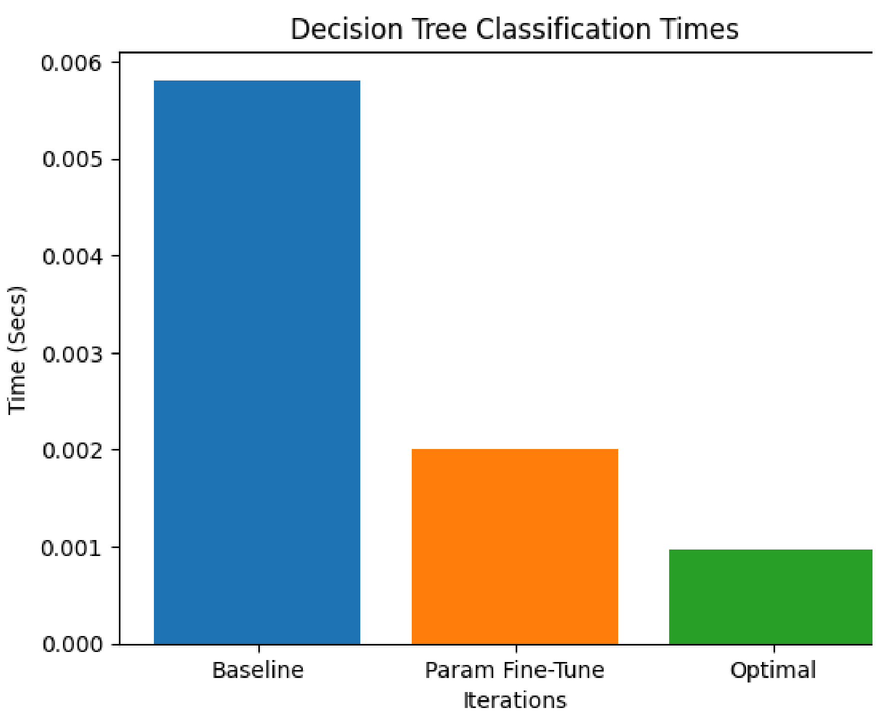
```
# Test the trained model using the test set
model_start = time.time()
model_pred = optimal_model.predict(X_test_selected)
model_end = time.time()

# Calculate prediction time
model_pred_time = model_end - model_start

print("DT Prediction Time: ", model_pred_time)
print("DT Accuracy:",  accuracy_score(y_test, model_pred))
print("DT F1-score:", f1_score(y_test, model_pred, pos_label = 'Phishing'))
```

```
DT Prediction Time:  0.0009722709655761719
DT Accuracy: 0.9896907216494846
DT F1-score: 0.9904761904761905
```

```
# Create a PrettyTable object
table = PrettyTable()

# Define column names
table.field_names = ["Iteration", "Model / Algorithm", "Prediction Time", "Accuracy", "F1-Score"]

# Add rows to the table
table.add_row(["Baseline", "DT", dt_pred_time, accuracy_score(y_test, dtree_pred), f1_score(y_test, dtree_pred, pos_
table.add_row(["Param Fine-Tune", "DT", dt_model_pred_time, accuracy_score(y_test, dt_model_pred), f1_score(y_test,
table.add_row(["Optimal", "DT", model_pred_time, accuracy_score(y_test, model_pred), f1_score(y_test, model_pred, pc

print(table)
```

```
+-----------------+-------------------+----------------------+--------------------+--------------------+
|    Iteration    | Model / Algorithm |   Prediction Time    |      Accuracy      |      F1-Score      |
+-----------------+-------------------+----------------------+--------------------+--------------------+
|     Baseline    |         DT        | 0.005805492401123047 | 0.9896907216494846 | 0.9904761904761905 |
| Param Fine-Tune |         DT        | 0.002010345458984375 | 0.9896907216494846 | 0.9904761904761905 |
|     Optimal     |         DT        | 0.0009722709655761719 | 0.9896907216494846 | 0.9904761904761905 |
+-----------------+-------------------+----------------------+--------------------+--------------------+
```

```
# Create bar chart using extracted values from table
plt.bar("Baseline", dt_pred_time)
plt.bar("Param Fine-Tune", dt_model_pred_time)
plt.bar("Optimal", model_pred_time)

# Define chart labels
plt.title("Decision Tree Classification Times")
plt.xlabel("Iterations")
plt.ylabel("Time (Secs)")

# Show plot
plt.show()
```



Save Trained Model w/ top 10 Best Features:

1. domain_similarity

2. url_length
3. http_protocol
4. num_slash
5. num_hyphen
6. response_history
7. redirect
8. num_a_href
9. num_link_href
10. num_iframe

```
import joblib
```