dodia_jaysheel_finaltermproj

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[73]:
```
from IPython.display import Image
```

1 CS634 Fall Final Project

Name: Jaysheel Dodia UCID: jd849 MailID: jd849@njit.edu Date: 24/11/2024 (DD/MM/YYYY)
Instructur: Dr. Yasser Abduallah Class: CS634-101

2 Abstract

In this project we will perform classification of emails into "spam" and "ham" categories using Machine Learning and Deep Learning, specifically using Random Forest Classification, Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) neural networks. The goal is to develop a model which effectively classifies the email as a "spam" or a "ham" using Random Forest, SVM and LSTM. This project uses publicly available Spam Classification Dataset. We implement data preprocessing techniques, and evaluates the models' performance using metrics such as accuracy, precision, recall, and F1-score. We also perform K-Fold validation on the dataset on each of the 3 algorithms and compare the resutls using the evaluation metrics.

3 Introduction

In this project applies multiple Machine Learning and Deep Learning algorithms - Random Forest Classification, Support Vector Machine and Long Short-Term Memory (LSTM) network - to classify emails as "spam" or "ham". The project involves preprocessing a publicly available dataset, training multiple models using K-Fold Cross Validation, and evaluating performance using metrics. By doing this we are able to compare the performance of different models and their effectiveness for training a text-classification model.

4 Methods

4.1 Random Forest Classification

Random Forest is an ensemble learning algorithm works by creating multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees. It is an extension of the Decision Tree algorithm and is widely used due to its simplicity, flexibility, and robustness. Random Forest overcomes many of the limitations of a single decision tree by combining the predictions of multiple trees. This reduces the risk of overfitting and improving predictive performance.

4.2 Support Vector Machine (SVM)

A support vector machine (SVM) is a supervised machine learning algorithm that classifies data by finding an optimal line or hyperplane that maximizes the distance between each class in an N-dimensional space. It works by diving the virtual plane into maximum separating hyperplane between the different classes in the target feature, making them suitable for classification tasks.

4.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory is an improved version of recurrent neural network (RNN). Learning long-term dependencies might be challenging for a typical RNN because it only has one hidden state that is transferred through time. The memory cell, a container that can store information for a long time, is introduced in the LSTM model to solve this issue.

4.4 Dataset

The Spam Ham text classification dataset is a widely used collection of text messages or emails labeled as either spam (unwanted/harmful) or ham (legitimate). This dataset serves as a valuable resource for developing and evaluating machine learning and deep learning models in natural language processing tasks, particularly for spam detection and text classification. The dataset can be downloaded from the following link: Dataset Link

4.5 Libraries Used

Library	Usage	Version
Numpy	For matrix operations	2.0.2
Pandas	Data manipulations and analysis	2.2.3
Matplotlib	Graph Plotting library	3.9.2
Seaborn	High-level plotting based on Matplotlib	0.13.2
Scikit-Learn	Machine Learning and Data Pre-processing	1.5.2
Tensorflow	Build Neural Network and LSTM	2.18.0

4.6 Prerequisite

1. Open up a terminal in our project directory (Refer Screenshot 1)
2. Now create a python virtual environment using the code `python -m venv venv` (Refer screenshot 2)
3. Now we will activate the environment to use it using the command `.\venv\Scripts\activate` if you're on windows. If you're on linux activate the environment using the command `source venv/bin/activate` (Refer Screenshot 3. I am using windows).
4. Once activated, install the requirements for our project using the command `pip install -r requirements.txt`. (Refer Screenshot 4)
5. Now, we can execute our python file by writing `python dodia_jaysheel_finaltermproj.py`. (Refer Screenshot 5)

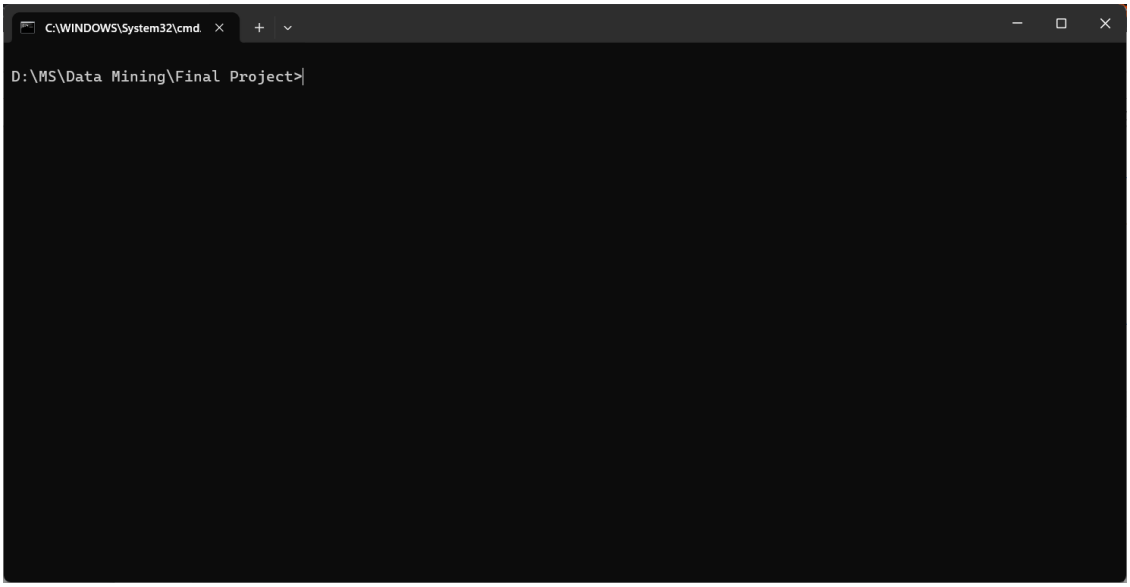
4.7 Note

- The graph plots used for visualization may be displayed differently while running the python file compared to the jupyter notebook. This is due to a change in the visual environment.
- On running the python file, when the graphs are generated, you will have to close the graph's window for the script to execute further. This happens because the `plt.show()` function blocks the terminal execution as long as the graph is being displayed. Close the graph window to continue.

Screenshot 1

[74]:
```
Image('ss/1.png')
```

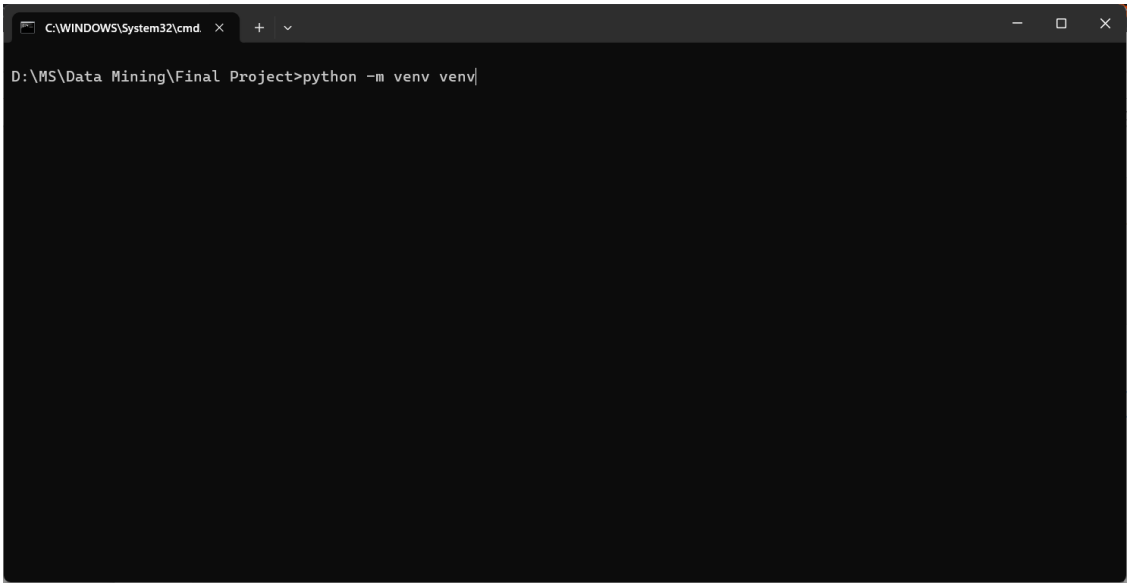
[74]:



Screenshot 2

[75]:
```
Image('ss/2.png')
```

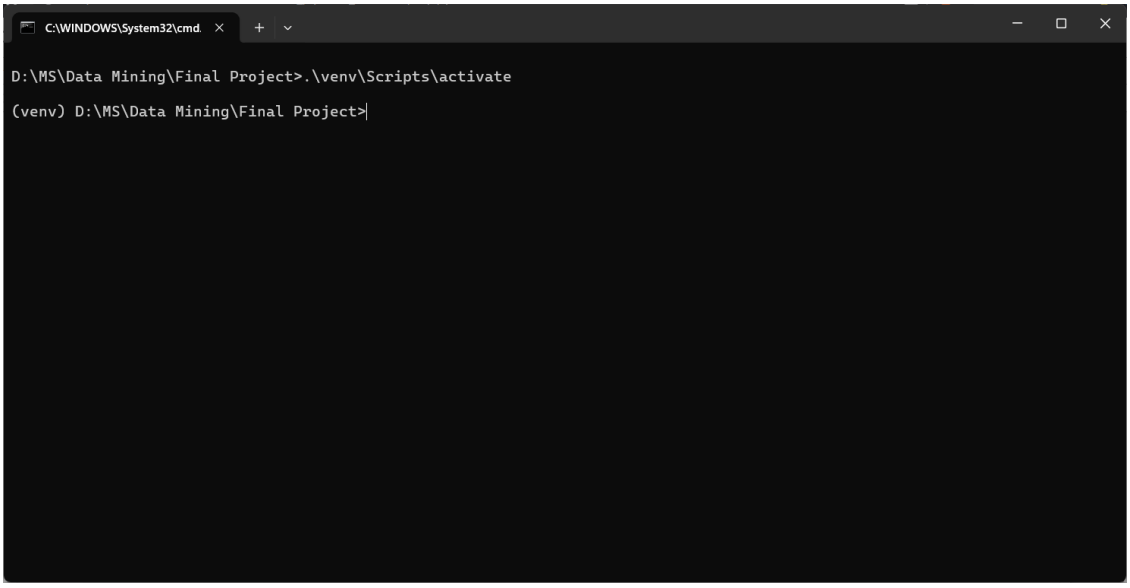
[75]:



Screenshot 3

[76]:
```
Image('ss/3.png')
```

[76]:



Screenshot 4

[77]:
```
Image('ss/4.png')
```

[77]:

```
C:\WINDOWS\System32\cmd.

(venv) D:\MS\Data Mining\Final Project>pip install -r requirements.txt
Requirement already satisfied: absl-py==2.1.0 in d:\ms\data mining\final project\venv\lib\site-packages (from -r require
ments.txt (line 1)) (2.1.0)
Requirement already satisfied: annotated-types==0.7.0 in d:\ms\data mining\final project\venv\lib\site-packages (from -r
 requirements.txt (line 2)) (0.7.0)
Requirement already satisfied: asttokens==2.4.1 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requi
rements.txt (line 3)) (2.4.1)
Requirement already satisfied: astunparse==1.6.3 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requ
irements.txt (line 4)) (1.6.3)
Requirement already satisfied: blis==1.0.1 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requiremen
ts.txt (line 5)) (1.0.1)
Requirement already satisfied: catalogue==2.0.10 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requ
irements.txt (line 6)) (2.0.10)
Requirement already satisfied: certifi==2024.8.30 in d:\ms\data mining\final project\venv\lib\site-packages (from -r req
uirements.txt (line 7)) (2024.8.30)
Requirement already satisfied: charset-normalizer==3.4.0 in d:\ms\data mining\final project\venv\lib\site-packages (from
 -r requirements.txt (line 8)) (3.4.0)
Requirement already satisfied: click==8.1.7 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requireme
nts.txt (line 9)) (8.1.7)
Requirement already satisfied: cloudpathlib==0.20.0 in d:\ms\data mining\final project\venv\lib\site-packages (from -r r
equirements.txt (line 10)) (0.20.0)
Requirement already satisfied: colorama==0.4.6 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requir
ements.txt (line 11)) (0.4.6)
Requirement already satisfied: comm==0.2.2 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requiremen
ts.txt (line 12)) (0.2.2)
Requirement already satisfied: confection==0.1.5 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requ
irements.txt (line 13)) (0.1.5)
Requirement already satisfied: contourpy==1.3.1 in d:\ms\data mining\final project\venv\lib\site-packages (from -r requi
rements.txt (line 14)) (1.3.1)
```

Screenshot 5

[78]:
```
Image('ss/5.png')
```

[78]:

```
Command Prompt - python c

(venv) D:\MS\Data Mining\Final Project>python dodia_jaysheel_finaltermproj.py
2024-11-24 00:47:13.586085: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly di
fferent numerical results due to floating-point round-off errors from different computation orders. To turn them off, se
t the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2024-11-24 00:47:14.630728: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly di
fferent numerical results due to floating-point round-off errors from different computation orders. To turn them off, se
t the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
Starting Random Forest Training
--------------------
Training Fold 1
Metrics for Fold  1
Confusion Matrix
[[ 24   0]
 [  6 220]]
Number of True Positives  24
Number of False Positives  0
Number of True Negatives  220
Number of False Negatives  6
True Positive Rate  0.8
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2
Accuracy  0.976
Precision  1.0
Recall  0.8
F1 Score  0.888888888888889
AUC Score  0.9
Brier Score  0.024
Brier Skill Score  0.22727272727272727
```

5 Implementation

5.1 Import Libraries

Import all the required libraries to carry out preprocessing tasks, implement Machine Learning algorithms and build LSTM neural network.

[79]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, KFold
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix, brier_score_loss, roc_curve,␣
 ↪roc_auc_score

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Embedding
```

[80]:
```
# Set random seed
np.random.seed(42)
```

5.2 Load Dataset

- Loading the dataset to our pandas dataframe
- The dataset consists of 2 main columns: Messages and Category
- Message: Contains the data or text of our message
- Category: Specifies if the message is a spam or a ham

[81]:
```
df = pd.read_csv("./dataset/spam.csv", encoding="latin-1")
df.head()
```

[81]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only …	NaN	NaN	NaN
1	ham	Ok lar… Joking wif u oni…	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina…	NaN	NaN	NaN
3	ham	U dun say so early hor… U c already then say…	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro…	NaN	NaN	NaN

[82]:
```
df.columns
```

[82]:
```
Index(['v1', 'v2', 'Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], dtype='object')
```

5.3 Preprocess Columns

[83]:
```
cols_to_drop = ["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"]
df = df.drop(cols_to_drop, axis=1)
```

[84]:
```
df.columns = ["Category", "Message"]
```

[85]:
```
df.head()
```

[85]:

	Category	Message
0	ham	Go until jurong point, crazy.. Available only …
1	ham	Ok lar… Joking wif u oni…
2	spam	Free entry in 2 a wkly comp to win FA Cup fina…
3	ham	U dun say so early hor… U c already then say…
4	ham	Nah I don't think he goes to usf, he lives aro…

5.4 Reducing dataset size

Random sampling our dataset to extract 2,500 rows at random and reduce the size of our dataset.

[86]:
```
df = df.sample(2500)
```

[87]:
```
df.shape
```

[87]:
```
(2500, 2)
```

5.5 Label Encoding

Converting target variable to 0 and 1 instead of the text `ham` and `spam`. Set the target variable to 1 if the category is "spam" and 0 if the category is "ham"

[88]:
```
df['spam']=df['Category'].apply(lambda x: 1 if x=='spam' else 0)
df.head()
```

[88]:

	Category	Message	spam
3245	ham	Funny fact Nobody teaches volcanoes 2 erupt, t…	0
944	ham	I sent my scores to sophas and i had to do sec…	0
1044	spam	We know someone who you know that fancies you…	1
2484	ham	Only if you promise your getting out as SOON a…	0
812	spam	Congratulations ur awarded either å£500 of CD …	1

[89]:
```
df.sample(1)
```

[89]:

	Category	Message	spam
1556	ham	Good sleep is about rhythm. The person has to …	0

5.6 Preprocess - For ML

5.6.1 Count Vectorizer

Count Vectorizer converts a collection of text documents (a dataframe of rows in our case) to a matrix of token count.

[90]:
```
cv = CountVectorizer()
X_cv = cv.fit_transform(df['Message'])
y = df['spam']
```

5.7 Functions to Calculate Metrics

5.7.1 Function to create the confusion matrix

[91]:
```
def create_cm(tp, tn, fp, fn):
    cm = np.array([[tp, fp], [fn, tn]])
    return cm
```

5.7.2 Function to calculate Brier Skill Score (BSS)

[92]:
```
def calc_bss(y_test, bs):
    mean = np.mean(y_test)
    brier_ref = np.mean((y_test - mean) ** 2)
    bss = bs/brier_ref
    return bss
```

5.7.3 Function to calculate all metrics

[93]:
```
def calc_all_metrics(y_test, y_pred, i):
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()

    # Rate
    tpr = tp / (tp + fn)
    tnr = tn / (tn + fp)
    fpr = fp / (fp + tn)
    fnr = fn / (fn + tp)

    accuracy = (tp + tn) / (tp + tn + fp + fn)
    precision = tp / (tp + fp)
    recall = tp / (tp + fn)
    f1 = (2 * precision * recall) / (precision + recall)

    auc_score = roc_auc_score(y_test, y_pred)

    brier = brier_score_loss(y_test, y_pred)
    brier_skill_score = calc_bss(y_test, brier)

    cm = create_cm(tp, tn, fp, fn)
```

```
    print("Metrics for Fold ", i)
    print("-"*10)
    print("Confusion Matrix for Fold ", i)
    print(cm)
    print("Number of True Positives ", tp)
    print("Number of False Positives ", fp)
    print("Number of True Negatives ", tn)
    print("Number of False Negatives ", fn)
    print("True Positive Rate ", tpr)
    print("True Negative Rate ", tnr)
    print("False Positive Rate ", fpr)
    print("False Negative Rate ", fnr)
    print("Accuracy ", accuracy)
    print("Precision ", precision)
    print("Recall ", recall)
    print("F1 Score ", f1)
    print("AUC Score ", auc_score)
    print("Brier Score ", brier)
    print("Brier Skill Score ", brier_skill_score)
    print(f"Training for fold {i} completed")
    print("\n")


    fold = f"Fold {i}"
    return [fold, tp, tn, fp, fn, tpr, tnr, fpr, fnr, accuracy, precision,␣
↪recall, f1, auc_score, brier, brier_skill_score]
```

5.8 Plotting Function

Function to plot the AUC-ROC Curve for each fold of the model

[94]:
```
def plot_roc_curves_in_grid(roc_data, model_name):
    n_rows = int(np.ceil(len(roc_data) / 3))
    fig, axes = plt.subplots(n_rows, 3, figsize=(10, n_rows * 3))
    axes = axes.flatten()  # Flatten the axes to make indexing easier

    for i, (fpr, tpr, auc_score) in enumerate(roc_data):
        ax = axes[i]
        ax.plot(fpr, tpr, label=f"ROC Curve (AUC) score {auc_score:.2f}")
        ax.plot([0, 1], [0, 1], linestyle='--')  # Diagonal line (random␣
↪classifier)
        ax.set_xlabel('False Positive Rate')
        ax.set_ylabel('True Positive Rate')
        ax.set_title(f'{model_name} Fold {i + 1} ROC Curve')

    for j in range(i + 1, len(axes)):
```

```
        axes[j].axis('off')

    plt.tight_layout(pad=3.0)
    plt.show()
```

5.9 Creating 10-Fold

The dataset is divided into 10 equal parts (called folds), where each fold is used once as a test set while the remaining 9 folds are used as the training set.

[95]:
```
N_SPLITS = 10
kf = KFold(n_splits=N_SPLITS, shuffle=True, random_state=42)
```

5.10 Random Forest Classifier

[96]:
```
rf_metrics = []
rf_roc_data = []

print("-"*20)
print("Starting Random Forest Training")
print("-"*20)

# Loop through the 10Fold splits
for i, (train_index, test_index) in enumerate(kf.split(X_cv), start=1):
    # Splitting the data into train and test split
    X_train, X_test = X_cv[train_index], X_cv[test_index] # type: ignore
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    print(f"Training Fold {i}")

    # Training the model
    rf = RandomForestClassifier()
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)

    # Calculating the AUC-ROC curve and score
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    auc_score = roc_auc_score(y_test, y_pred)
    rf_roc_data.append((fpr, tpr, auc_score))

    # Calculate all the metrics and store them
    rf_metrics.append(calc_all_metrics(y_test, y_pred, i))
```

```
--------------------
Starting Random Forest Training
--------------------
Training Fold 1
Metrics for Fold  1
```

```
----------
Confusion Matrix for Fold  1
[[ 24   0]
 [  6 220]]
Number of True Positives  24
Number of False Positives  0
Number of True Negatives  220
Number of False Negatives  6
True Positive Rate  0.8
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2
Accuracy  0.976
Precision  1.0
Recall  0.8
F1 Score  0.888888888888889
AUC Score  0.9
Brier Score  0.024
Brier Skill Score  0.22727272727272727
Training for fold 1 completed


Training Fold 2
Metrics for Fold  2
----------
Confusion Matrix for Fold  2
[[ 22   0]
 [  7 221]]
Number of True Positives  22
Number of False Positives  0
Number of True Negatives  221
Number of False Negatives  7
True Positive Rate  0.7586206896551724
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2413793103448276
Accuracy  0.972
Precision  1.0
Recall  0.7586206896551724
F1 Score  0.8627450980392156
AUC Score  0.8793103448275862
Brier Score  0.028
Brier Skill Score  0.27305351848962395
Training for fold 2 completed


Training Fold 3
Metrics for Fold  3
```

```
----------
Confusion Matrix for Fold  3
[[ 25   1]
 [  5 219]]
Number of True Positives  25
Number of False Positives  1
Number of True Negatives  219
Number of False Negatives  5
True Positive Rate  0.8333333333333334
True Negative Rate  0.9954545454545455
False Positive Rate  0.004545454545454545
False Negative Rate  0.16666666666666666
Accuracy  0.976
Precision  0.9615384615384616
Recall  0.8333333333333334
F1 Score  0.8928571428571429
AUC Score  0.9143939393939395
Brier Score  0.024
Brier Skill Score  0.22727272727272724
Training for fold 3 completed


Training Fold 4
Metrics for Fold  4
----------
Confusion Matrix for Fold  4
[[ 17   0]
 [  5 228]]
Number of True Positives  17
Number of False Positives  0
Number of True Negatives  228
Number of False Negatives  5
True Positive Rate  0.7727272727272727
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.22727272727272727
Accuracy  0.98
Precision  1.0
Recall  0.7727272727272727
F1 Score  0.8717948717948718
AUC Score  0.8863636363636364
Brier Score  0.02
Brier Skill Score  0.24920255183413081
Training for fold 4 completed


Training Fold 5
Metrics for Fold  5
```

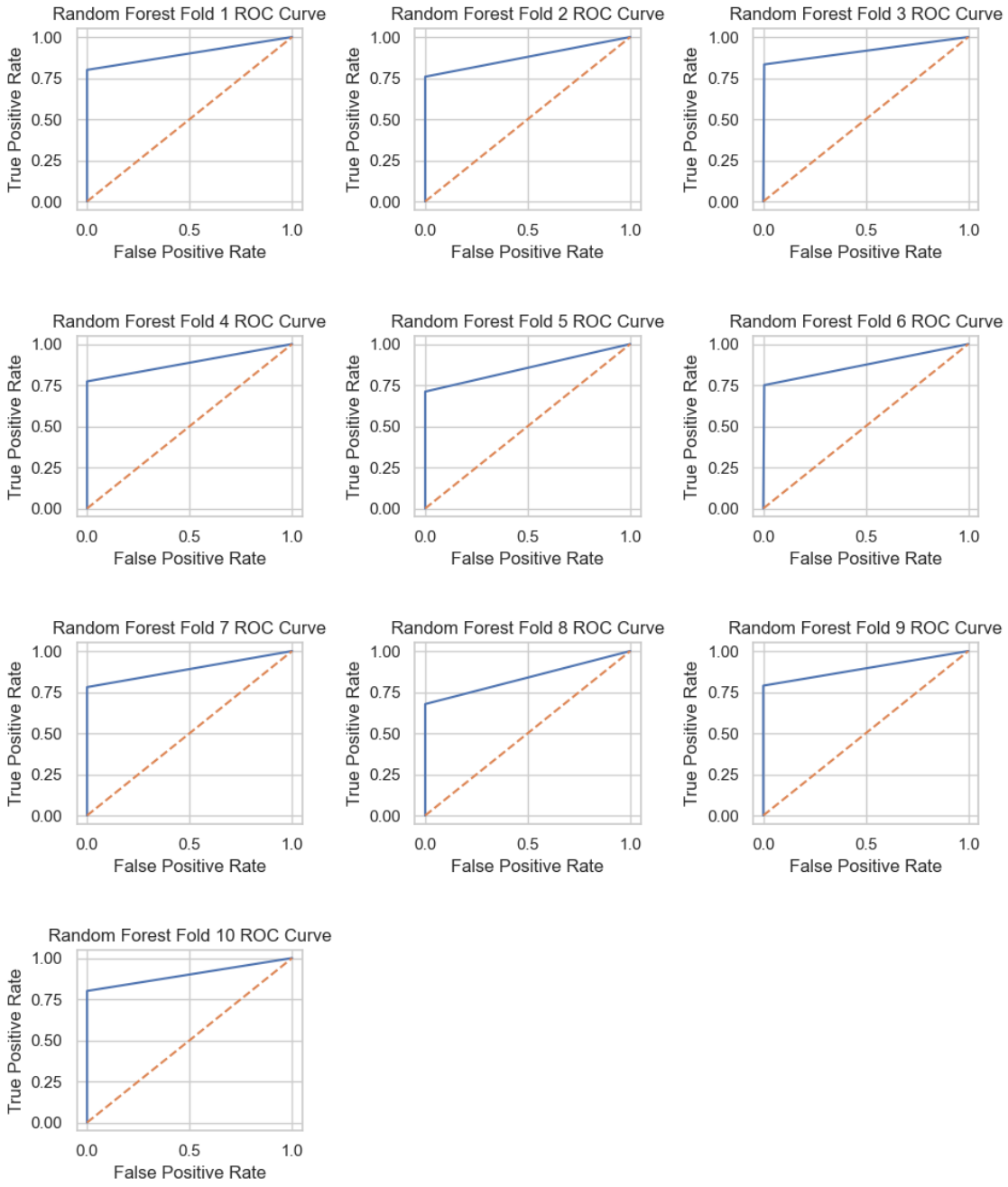
```
----------
Confusion Matrix for Fold  5
[[ 27   0]
 [ 11 212]]
Number of True Positives  27
Number of False Positives  0
Number of True Negatives  212
Number of False Negatives  11
True Positive Rate  0.7105263157894737
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2894736842105263
Accuracy  0.956
Precision  1.0
Recall  0.7105263157894737
F1 Score  0.8307692307692308
AUC Score  0.8552631578947368
Brier Score  0.044
Brier Skill Score  0.34136047666335645
Training for fold 5 completed


Training Fold 6
Metrics for Fold  6
----------
Confusion Matrix for Fold  6
[[ 27   1]
 [  9 213]]
Number of True Positives  27
Number of False Positives  1
Number of True Negatives  213
Number of False Negatives  9
True Positive Rate  0.75
True Negative Rate  0.9953271028037384
False Positive Rate  0.004672897196261682
False Negative Rate  0.25
Accuracy  0.96
Precision  0.9642857142857143
Recall  0.75
F1 Score  0.8437499999999999
AUC Score  0.8726635514018692
Brier Score  0.04
Brier Skill Score  0.3245067497403946
Training for fold 6 completed


Training Fold 7
Metrics for Fold  7
```

```
----------
Confusion Matrix for Fold  7
[[ 32   0]
 [  9 209]]
Number of True Positives  32
Number of False Positives  0
Number of True Negatives  209
Number of False Negatives  9
True Positive Rate  0.7804878048780488
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.21951219512195122
Accuracy  0.964
Precision  1.0
Recall  0.7804878048780488
F1 Score  0.8767123287671234
AUC Score  0.8902439024390244
Brier Score  0.036
Brier Skill Score  0.26257439607888905
Training for fold 7 completed


Training Fold 8
Metrics for Fold  8
----------
Confusion Matrix for Fold  8
[[ 21   0]
 [ 10 219]]
Number of True Positives  21
Number of False Positives  0
Number of True Negatives  219
Number of False Negatives  10
True Positive Rate  0.6774193548387096
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.3225806451612903
Accuracy  0.96
Precision  1.0
Recall  0.6774193548387096
F1 Score  0.8076923076923077
AUC Score  0.8387096774193548
Brier Score  0.04
Brier Skill Score  0.3682427456179113
Training for fold 8 completed


Training Fold 9
Metrics for Fold  9
```

```
----------
Confusion Matrix for Fold  9
[[ 30   0]
 [  8 212]]
Number of True Positives  30
Number of False Positives  0
Number of True Negatives  212
Number of False Negatives  8
True Positive Rate  0.7894736842105263
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.21052631578947367
Accuracy  0.968
Precision  1.0
Recall  0.7894736842105263
F1 Score  0.8823529411764706
AUC Score  0.8947368421052632
Brier Score  0.032
Brier Skill Score  0.24826216484607744
Training for fold 9 completed


Training Fold 10
Metrics for Fold  10
----------
Confusion Matrix for Fold  10
[[ 28   0]
 [  7 215]]
Number of True Positives  28
Number of False Positives  0
Number of True Negatives  215
Number of False Negatives  7
True Positive Rate  0.8
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2
Accuracy  0.972
Precision  1.0
Recall  0.8
F1 Score  0.888888888888889
AUC Score  0.9
Brier Score  0.028
Brier Skill Score  0.23255813953488375
Training for fold 10 completed
```

[97]:
```
# Add model name to column
for i, metric in enumerate(rf_metrics):
    metric.insert(0, 'Random Forest')
```

[98]:
```
plot_roc_curves_in_grid(rf_roc_data, "Random Forest")
```



5.11 SVM

[99]:
```
svm_metrics = []
svm_roc_data = []

print("-"*20)
print("Starting SVM Training")
print("-"*20)

# Loop through the KFold splits
for i, (train_index, test_index) in enumerate(kf.split(X_cv), start=1):
    # Splitting the data into train and test split
    X_train, X_test = X_cv[train_index], X_cv[test_index] # type: ignore
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    print(f"Training Fold {i}! ", end='')
    # Training the model
    svm = SVC()
    svm.fit(X_train, y_train)
    y_pred = svm.predict(X_test)

    # Calculating the AUC-ROC curve and score
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    auc_score = roc_auc_score(y_test, y_pred)
    svm_roc_data.append((fpr, tpr, auc_score))

    # Calculate metrics and storing them
    svm_metrics.append(calc_all_metrics(y_test, y_pred, i))
```

```
--------------------
Starting SVM Training
--------------------
Training Fold 1! Metrics for Fold  1
----------
Confusion Matrix for Fold  1
[[ 26   0]
 [  4 220]]
Number of True Positives  26
Number of False Positives  0
Number of True Negatives  220
Number of False Negatives  4
True Positive Rate  0.8666666666666667
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.13333333333333333
Accuracy  0.984
Precision  1.0
Recall  0.8666666666666667
```

```
F1 Score  0.9285714285714286
AUC Score  0.9333333333333333
Brier Score  0.016
Brier Skill Score  0.15151515151515152
Training for fold 1 completed


Training Fold 2! Metrics for Fold  2
----------
Confusion Matrix for Fold  2
[[ 25   0]
 [  4 221]]
Number of True Positives  25
Number of False Positives  0
Number of True Negatives  221
Number of False Negatives  4
True Positive Rate  0.8620689655172413
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.13793103448275862
Accuracy  0.984
Precision  1.0
Recall  0.8620689655172413
F1 Score  0.9259259259259259
AUC Score  0.9310344827586207
Brier Score  0.016
Brier Skill Score  0.15603058199407083
Training for fold 2 completed


Training Fold 3! Metrics for Fold  3
----------
Confusion Matrix for Fold  3
[[ 24   0]
 [  6 220]]
Number of True Positives  24
Number of False Positives  0
Number of True Negatives  220
Number of False Negatives  6
True Positive Rate  0.8
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2
Accuracy  0.976
Precision  1.0
Recall  0.8
F1 Score  0.888888888888889
AUC Score  0.9
```

```
Brier Score  0.024
Brier Skill Score  0.22727272727272724
Training for fold 3 completed


Training Fold 4! Metrics for Fold  4
----------
Confusion Matrix for Fold  4
[[ 16   0]
 [  6 228]]
Number of True Positives  16
Number of False Positives  0
Number of True Negatives  228
Number of False Negatives  6
True Positive Rate  0.7272727272727273
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2727272727272727
Accuracy  0.976
Precision  1.0
Recall  0.7272727272727273
F1 Score  0.8421052631578948
AUC Score  0.8636363636363636
Brier Score  0.024
Brier Skill Score  0.29904306220095694
Training for fold 4 completed


Training Fold 5! Metrics for Fold  5
----------
Confusion Matrix for Fold  5
[[ 28   0]
 [ 10 212]]
Number of True Positives  28
Number of False Positives  0
Number of True Negatives  212
Number of False Negatives  10
True Positive Rate  0.7368421052631579
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2631578947368421
Accuracy  0.96
Precision  1.0
Recall  0.7368421052631579
F1 Score  0.8484848484848484
AUC Score  0.868421052631579
Brier Score  0.04
Brier Skill Score  0.3103277060575968
```

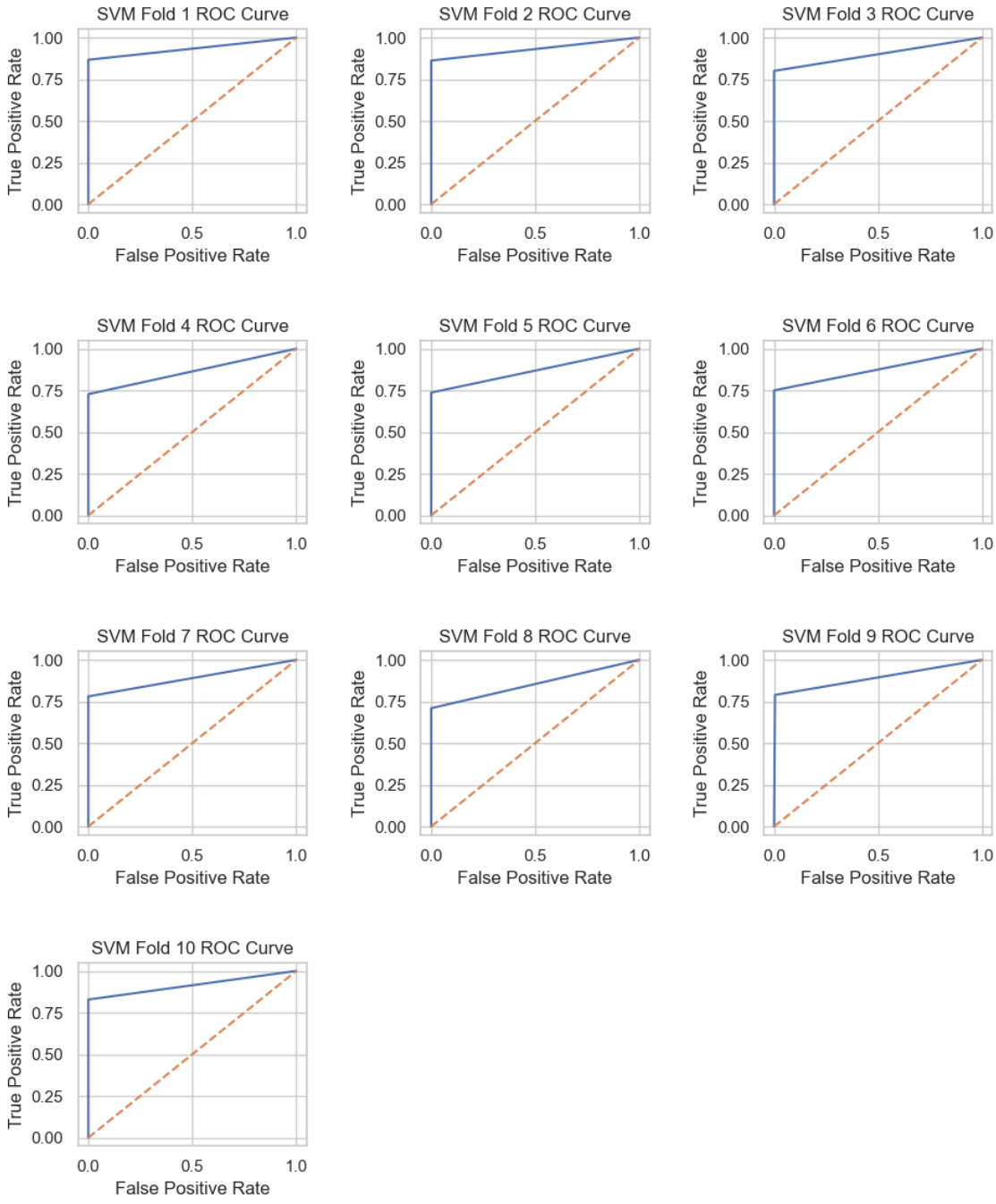
```
Training for fold 5 completed


Training Fold 6! Metrics for Fold  6
----------
Confusion Matrix for Fold  6
[[ 27   0]
 [  9 214]]
Number of True Positives  27
Number of False Positives  0
Number of True Negatives  214
Number of False Negatives  9
True Positive Rate  0.75
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.25
Accuracy  0.964
Precision  1.0
Recall  0.75
F1 Score  0.8571428571428571
AUC Score  0.875
Brier Score  0.036
Brier Skill Score  0.29205607476635514
Training for fold 6 completed


Training Fold 7! Metrics for Fold  7
----------
Confusion Matrix for Fold  7
[[ 32   0]
 [  9 209]]
Number of True Positives  32
Number of False Positives  0
Number of True Negatives  209
Number of False Negatives  9
True Positive Rate  0.7804878048780488
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.21951219512195122
Accuracy  0.964
Precision  1.0
Recall  0.7804878048780488
F1 Score  0.8767123287671234
AUC Score  0.8902439024390244
Brier Score  0.036
Brier Skill Score  0.26257439607888905
Training for fold 7 completed
```

```
Training Fold 8! Metrics for Fold  8
----------
Confusion Matrix for Fold  8
[[ 22   0]
 [  9 219]]
Number of True Positives  22
Number of False Positives  0
Number of True Negatives  219
Number of False Negatives  9
True Positive Rate  0.7096774193548387
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.2903225806451613
Accuracy  0.964
Precision  1.0
Recall  0.7096774193548387
F1 Score  0.8301886792452831
AUC Score  0.8548387096774194
Brier Score  0.036
Brier Skill Score  0.33141847105612016
Training for fold 8 completed


Training Fold 9! Metrics for Fold  9
----------
Confusion Matrix for Fold  9
[[ 30   1]
 [  8 211]]
Number of True Positives  30
Number of False Positives  1
Number of True Negatives  211
Number of False Negatives  8
True Positive Rate  0.7894736842105263
True Negative Rate  0.9952830188679245
False Positive Rate  0.0047169811320754715
False Negative Rate  0.21052631578947367
Accuracy  0.964
Precision  0.967741935483871
Recall  0.7894736842105263
F1 Score  0.8695652173913043
AUC Score  0.8923783515392254
Brier Score  0.036
Brier Skill Score  0.2792949354518371
Training for fold 9 completed


Training Fold 10! Metrics for Fold  10
```

```
----------
Confusion Matrix for Fold  10
[[ 29   0]
 [  6 215]]
Number of True Positives  29
Number of False Positives  0
Number of True Negatives  215
Number of False Negatives  6
True Positive Rate  0.8285714285714286
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.17142857142857143
Accuracy  0.976
Precision  1.0
Recall  0.8285714285714286
F1 Score  0.90625
AUC Score  0.9142857142857144
Brier Score  0.024
Brier Skill Score  0.1993355481727575
Training for fold 10 completed
```

[100]:
```python
# add the model name to the metrics
for i, metric in enumerate(svm_metrics):
    metric.insert(0, 'SVM')
```

[101]:
```python
plot_roc_curves_in_grid(svm_roc_data, "SVM")
```



5.12 Preprocess for LSTM

[102]:
```
X = df['Message']
y = df['spam']
```

Break the text into tokens and make them suitable for training an LSTM.

[103]:
```
# Tokenization
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X)
X_tok= tokenizer.texts_to_sequences(X)

# Padding the data
X_pad = pad_sequences(X_tok)
```

5.13 LSTM

5.13.1 Function to build LSTM model

[104]:
```
def build_model(X_train_pad):
    # Training the model
    model = Sequential()
    model.add(Embedding(input_dim=len(tokenizer.word_index)+1, output_dim=32))
    model.add(LSTM(32))
    model.add(Dense(1, activation='sigmoid'))
    return model
```

5.13.2 Executing

[105]:
```
lstm_metrics = []
lstm_roc_data = []
print("-"*20)
print("Starting LSTM Training")
print("-"*20)
for i, (train_index, test_index) in enumerate(kf.split(X_pad), start=1):
    # Splitting the data into train and test split
    X_train, X_test = X_pad[train_index], X_pad[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # train the LSTM model
    model = build_model(X_train)

    model.compile(loss='binary_crossentropy', optimizer='adam')

    model.fit(X_train, y_train, epochs=2, batch_size=32, verbose=0)
    y_pred = model.predict(X_test, verbose=0) > 0.5

    # Calculating the AUC-ROC score and curve
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    auc_score = roc_auc_score(y_test, y_pred)
    lstm_roc_data.append((fpr, tpr, auc_score))

    # calculating the metrics and storing them
    lstm_metrics.append(calc_all_metrics(y_test, y_pred, i))
```

```
--------------------
Starting LSTM Training
--------------------
Metrics for Fold  1
----------
Confusion Matrix for Fold  1
[[ 26   1]
 [  4 219]]
Number of True Positives  26
Number of False Positives  1
Number of True Negatives  219
Number of False Negatives  4
True Positive Rate  0.8666666666666667
True Negative Rate  0.9954545454545455
False Positive Rate  0.004545454545454545
False Negative Rate  0.13333333333333333
Accuracy  0.98
Precision  0.9629629629629629
Recall  0.8666666666666667
F1 Score  0.912280701754386
AUC Score  0.931060606060606
```

```
Brier Score  0.02
Brier Skill Score  0.1893939393939394
Training for fold 1 completed


Metrics for Fold  2
----------
Confusion Matrix for Fold  2
[[ 27   0]
 [  2 221]]
Number of True Positives  27
Number of False Positives  0
Number of True Negatives  221
Number of False Negatives  2
True Positive Rate  0.9310344827586207
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.06896551724137931
Accuracy  0.992
Precision  1.0
Recall  0.9310344827586207
F1 Score  0.9642857142857143
AUC Score  0.9655172413793103
Brier Score  0.008
Brier Skill Score  0.07801529099703541
Training for fold 2 completed


Metrics for Fold  3
----------
Confusion Matrix for Fold  3
[[ 25   1]
 [  5 219]]
Number of True Positives  25
Number of False Positives  1
Number of True Negatives  219
Number of False Negatives  5
True Positive Rate  0.8333333333333334
True Negative Rate  0.9954545454545455
False Positive Rate  0.004545454545454545
False Negative Rate  0.16666666666666666
Accuracy  0.976
Precision  0.9615384615384616
Recall  0.8333333333333334
F1 Score  0.8928571428571429
AUC Score  0.9143939393939395
Brier Score  0.024
Brier Skill Score  0.22727272727272724
```

```
Training for fold 3 completed


Metrics for Fold  4
----------
Confusion Matrix for Fold  4
[[ 19   0]
 [  3 228]]
Number of True Positives  19
Number of False Positives  0
Number of True Negatives  228
Number of False Negatives  3
True Positive Rate  0.8636363636363636
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.13636363636363635
Accuracy  0.988
Precision  1.0
Recall  0.8636363636363636
F1 Score  0.9268292682926829
AUC Score  0.9318181818181819
Brier Score  0.012
Brier Skill Score  0.14952153110047847
Training for fold 4 completed


Metrics for Fold  5
----------
Confusion Matrix for Fold  5
[[ 30   0]
 [  8 212]]
Number of True Positives  30
Number of False Positives  0
Number of True Negatives  212
Number of False Negatives  8
True Positive Rate  0.7894736842105263
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.21052631578947367
Accuracy  0.968
Precision  1.0
Recall  0.7894736842105263
F1 Score  0.8823529411764706
AUC Score  0.8947368421052632
Brier Score  0.032
Brier Skill Score  0.24826216484607744
Training for fold 5 completed
```

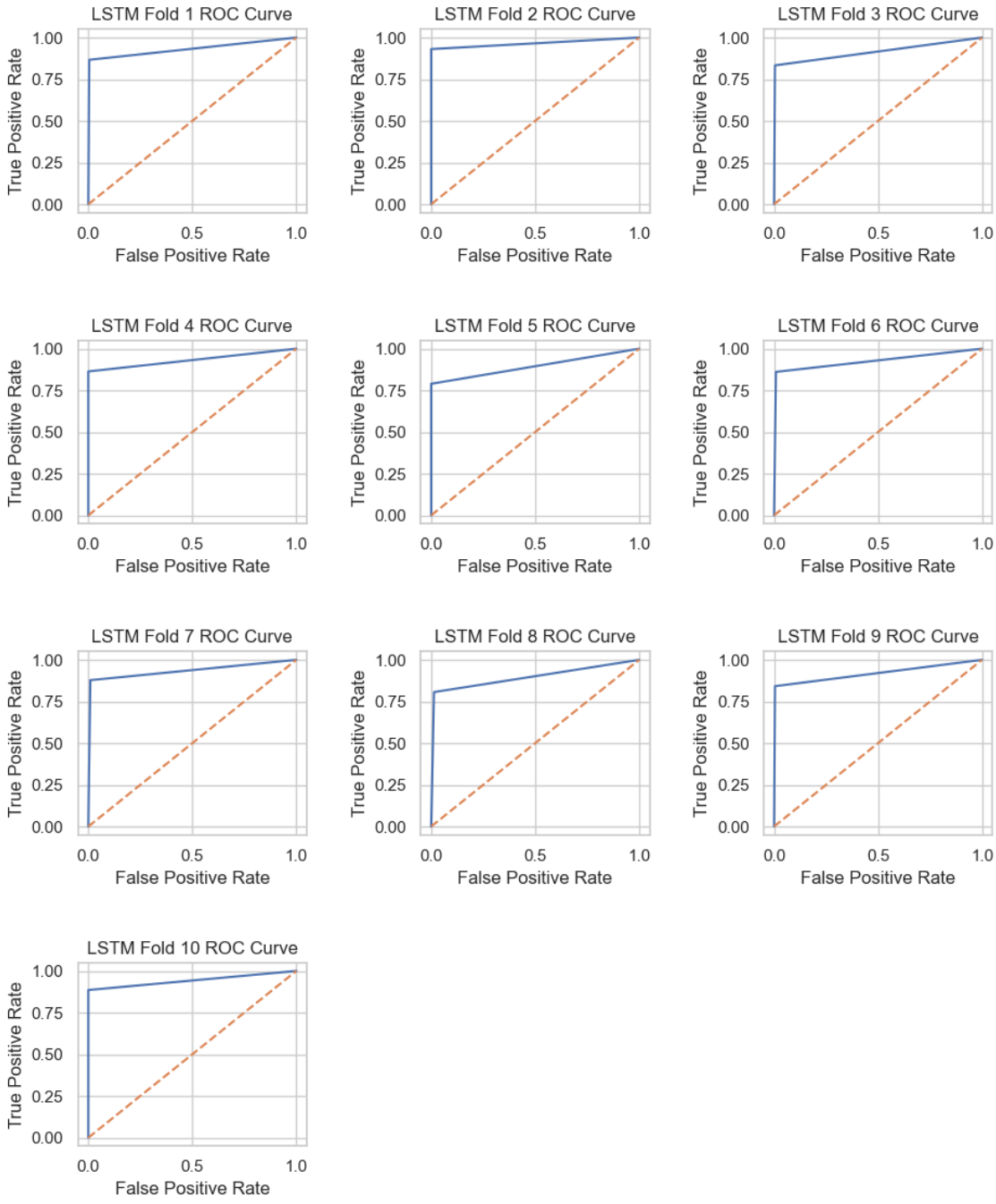
```
Metrics for Fold  6
----------
Confusion Matrix for Fold  6
[[ 31   2]
 [  5 212]]
Number of True Positives  31
Number of False Positives  2
Number of True Negatives  212
Number of False Negatives  5
True Positive Rate  0.8611111111111112
True Negative Rate  0.9906542056074766
False Positive Rate  0.009345794392523364
False Negative Rate  0.1388888888888889
Accuracy  0.972
Precision  0.9393939393939394
Recall  0.8611111111111112
F1 Score  0.8985507246376813
AUC Score  0.9258826583592938
Brier Score  0.028
Brier Skill Score  0.22715472481827623
Training for fold 6 completed


Metrics for Fold  7
----------
Confusion Matrix for Fold  7
[[ 36   2]
 [  5 207]]
Number of True Positives  36
Number of False Positives  2
Number of True Negatives  207
Number of False Negatives  5
True Positive Rate  0.8780487804878049
True Negative Rate  0.9904306220095693
False Positive Rate  0.009569377990430622
False Negative Rate  0.12195121951219512
Accuracy  0.972
Precision  0.9473684210526315
Recall  0.8780487804878049
F1 Score  0.9113924050632912
AUC Score  0.9342397012486869
Brier Score  0.028
Brier Skill Score  0.2042245302835804
Training for fold 7 completed


Metrics for Fold  8
```

```
----------
Confusion Matrix for Fold  8
[[ 25   3]
 [  6 216]]
Number of True Positives  25
Number of False Positives  3
Number of True Negatives  216
Number of False Negatives  6
True Positive Rate  0.8064516129032258
True Negative Rate  0.9863013698630136
False Positive Rate  0.0136986301369863
False Negative Rate  0.1935483870967742
Accuracy  0.964
Precision  0.8928571428571429
Recall  0.8064516129032258
F1 Score  0.8474576271186439
AUC Score  0.8963764913831196
Brier Score  0.036
Brier Skill Score  0.33141847105612016
Training for fold 8 completed


Metrics for Fold  9
----------
Confusion Matrix for Fold  9
[[ 32   1]
 [  6 211]]
Number of True Positives  32
Number of False Positives  1
Number of True Negatives  211
Number of False Negatives  6
True Positive Rate  0.8421052631578947
True Negative Rate  0.9952830188679245
False Positive Rate  0.0047169811320754715
False Negative Rate  0.15789473684210525
Accuracy  0.972
Precision  0.9696969696969697
Recall  0.8421052631578947
F1 Score  0.9014084507042254
AUC Score  0.9186941410129096
Brier Score  0.028
Brier Skill Score  0.21722939424031776
Training for fold 9 completed


Metrics for Fold  10
----------
Confusion Matrix for Fold  10
```

```
[[ 31   0]
 [  4 215]]
Number of True Positives  31
Number of False Positives  0
Number of True Negatives  215
Number of False Negatives  4
True Positive Rate  0.8857142857142857
True Negative Rate  1.0
False Positive Rate  0.0
False Negative Rate  0.11428571428571428
Accuracy  0.984
Precision  1.0
Recall  0.8857142857142857
F1 Score  0.9393939393939393
AUC Score  0.9428571428571428
Brier Score  0.016
Brier Skill Score  0.132890365448505
Training for fold 10 completed
```

[106]:
```python
for i, metric in enumerate(lstm_metrics):
    metric.insert(0, 'LSTM')
```

[107]:
```python
plot_roc_curves_in_grid(lstm_roc_data, "LSTM")
```



5.14 Tabulate

Store the data into table format using pandas dataframe

[108]:
```
columns = ['ModelName', 'Fold', 'TP', 'TN', 'FP', 'FN', 'TPR', 'TNR',
           'FPR', 'FNR', 'Accuracy', 'Precision',
           'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']
```

```
rf_metrics_df = pd.DataFrame(rf_metrics, columns=columns)
svm_metrics_df = pd.DataFrame(svm_metrics, columns=columns)
lstm_metrics_df = pd.DataFrame(lstm_metrics, columns=columns)
```

5.14.1 Metrics in Table Format

Random Forest Classifier

[109]:
```
rf_metrics_df
```

[109]:

	ModelName	Fold	TP	TN	FP	FN	TPR	TNR	FPR
0	Random Forest	Fold 1	24	220	0	6	0.800000	1.000000	0.000000
1	Random Forest	Fold 2	22	221	0	7	0.758621	1.000000	0.000000
2	Random Forest	Fold 3	25	219	1	5	0.833333	0.995455	0.004545
3	Random Forest	Fold 4	17	228	0	5	0.772727	1.000000	0.000000
4	Random Forest	Fold 5	27	212	0	11	0.710526	1.000000	0.000000
5	Random Forest	Fold 6	27	213	1	9	0.750000	0.995327	0.004673
6	Random Forest	Fold 7	32	209	0	9	0.780488	1.000000	0.000000
7	Random Forest	Fold 8	21	219	0	10	0.677419	1.000000	0.000000
8	Random Forest	Fold 9	30	212	0	8	0.789474	1.000000	0.000000
9	Random Forest	Fold 10	28	215	0	7	0.800000	1.000000	0.000000

	FNR	Accuracy	Precision	Recall	F1	AUC	Brier
0	0.200000	0.976	1.000000	0.800000	0.888889	0.900000	0.024
1	0.241379	0.972	1.000000	0.758621	0.862745	0.879310	0.028
2	0.166667	0.976	0.961538	0.833333	0.892857	0.914394	0.024
3	0.227273	0.980	1.000000	0.772727	0.871795	0.886364	0.020
4	0.289474	0.956	1.000000	0.710526	0.830769	0.855263	0.044
5	0.250000	0.960	0.964286	0.750000	0.843750	0.872664	0.040
6	0.219512	0.964	1.000000	0.780488	0.876712	0.890244	0.036
7	0.322581	0.960	1.000000	0.677419	0.807692	0.838710	0.040
8	0.210526	0.968	1.000000	0.789474	0.882353	0.894737	0.032
9	0.200000	0.972	1.000000	0.800000	0.888889	0.900000	0.028

	Brier Skill Score
0	0.227273
1	0.273054
2	0.227273
3	0.249203
4	0.341360
5	0.324507
6	0.262574
7	0.368243
8	0.248262
9	0.232558

SVM

[110]:
```
svm_metrics_df
```

[110]:

	ModelName	Fold	TP	TN	FP	FN	TPR	TNR	FPR	FNR
0	SVM	Fold 1	26	220	0	4	0.866667	1.000000	0.000000	0.133333
1	SVM	Fold 2	25	221	0	4	0.862069	1.000000	0.000000	0.137931
2	SVM	Fold 3	24	220	0	6	0.800000	1.000000	0.000000	0.200000
3	SVM	Fold 4	16	228	0	6	0.727273	1.000000	0.000000	0.272727
4	SVM	Fold 5	28	212	0	10	0.736842	1.000000	0.000000	0.263158
5	SVM	Fold 6	27	214	0	9	0.750000	1.000000	0.000000	0.250000
6	SVM	Fold 7	32	209	0	9	0.780488	1.000000	0.000000	0.219512
7	SVM	Fold 8	22	219	0	9	0.709677	1.000000	0.000000	0.290323
8	SVM	Fold 9	30	211	1	8	0.789474	0.995283	0.004717	0.210526
9	SVM	Fold 10	29	215	0	6	0.828571	1.000000	0.000000	0.171429

	Accuracy	Precision	Recall	F1	AUC	Brier	Brier Skill Score
0	0.984	1.000000	0.866667	0.928571	0.933333	0.016	0.151515
1	0.984	1.000000	0.862069	0.925926	0.931034	0.016	0.156031
2	0.976	1.000000	0.800000	0.888889	0.900000	0.024	0.227273
3	0.976	1.000000	0.727273	0.842105	0.863636	0.024	0.299043
4	0.960	1.000000	0.736842	0.848485	0.868421	0.040	0.310328
5	0.964	1.000000	0.750000	0.857143	0.875000	0.036	0.292056
6	0.964	1.000000	0.780488	0.876712	0.890244	0.036	0.262574
7	0.964	1.000000	0.709677	0.830189	0.854839	0.036	0.331418
8	0.964	0.967742	0.789474	0.869565	0.892378	0.036	0.279295
9	0.976	1.000000	0.828571	0.906250	0.914286	0.024	0.199336

LSTM

[111]:
```
lstm_metrics_df
```

[111]:

	ModelName	Fold	TP	TN	FP	FN	TPR	TNR	FPR	FNR
0	LSTM	Fold 1	26	219	1	4	0.866667	0.995455	0.004545	0.133333
1	LSTM	Fold 2	27	221	0	2	0.931034	1.000000	0.000000	0.068966
2	LSTM	Fold 3	25	219	1	5	0.833333	0.995455	0.004545	0.166667
3	LSTM	Fold 4	19	228	0	3	0.863636	1.000000	0.000000	0.136364
4	LSTM	Fold 5	30	212	0	8	0.789474	1.000000	0.000000	0.210526
5	LSTM	Fold 6	31	212	2	5	0.861111	0.990654	0.009346	0.138889
6	LSTM	Fold 7	36	207	2	5	0.878049	0.990431	0.009569	0.121951
7	LSTM	Fold 8	25	216	3	6	0.806452	0.986301	0.013699	0.193548
8	LSTM	Fold 9	32	211	1	6	0.842105	0.995283	0.004717	0.157895
9	LSTM	Fold 10	31	215	0	4	0.885714	1.000000	0.000000	0.114286

	Accuracy	Precision	Recall	F1	AUC	Brier	Brier Skill Score
0	0.980	0.962963	0.866667	0.912281	0.931061	0.020	0.189394
1	0.992	1.000000	0.931034	0.964286	0.965517	0.008	0.078015
2	0.976	0.961538	0.833333	0.892857	0.914394	0.024	0.227273
3	0.988	1.000000	0.863636	0.926829	0.931818	0.012	0.149522
4	0.968	1.000000	0.789474	0.882353	0.894737	0.032	0.248262
5	0.972	0.939394	0.861111	0.898551	0.925883	0.028	0.227155
6	0.972	0.947368	0.878049	0.911392	0.934240	0.028	0.204225

```
7     0.964   0.892857  0.806452  0.847458  0.896376  0.036           0.331418
8     0.972   0.969697  0.842105  0.901408  0.918694  0.028           0.217229
9     0.984   1.000000  0.885714  0.939394  0.942857  0.016           0.132890
```

[112]:
```
# combine all the dataframes
all_metrics = pd.concat([rf_metrics_df, svm_metrics_df, lstm_metrics_df],␣
 ↪axis=0)
all_metrics.reset_index(drop=True, inplace=True)
all_metrics
```

[112]:

	ModelName	Fold	TP	TN	FP	FN	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F1	AUC	Brier
0	Random Forest	Fold 1	24	220	0	6	0.800000	1.000000	0.000000	0.200000	0.976	1.000000	0.800000	0.888889	0.900000	0.024
1	Random Forest	Fold 2	22	221	0	7	0.758621	1.000000	0.000000	0.241379	0.972	1.000000	0.758621	0.862745	0.879310	0.028
2	Random Forest	Fold 3	25	219	1	5	0.833333	0.995455	0.004545	0.166667	0.976	0.961538	0.833333	0.892857	0.914394	0.024
3	Random Forest	Fold 4	17	228	0	5	0.772727	1.000000	0.000000	0.227273	0.980	1.000000	0.772727	0.871795	0.886364	0.020
4	Random Forest	Fold 5	27	212	0	11	0.710526	1.000000	0.000000	0.289474	0.956	1.000000	0.710526	0.830769	0.855263	0.044
5	Random Forest	Fold 6	27	213	1	9	0.750000	0.995327	0.004673	0.250000	0.960	0.964286	0.750000	0.843750	0.872663	0.040
6	Random Forest	Fold 7	32	209	0	9	0.780488	1.000000	0.000000	0.219512	0.964	1.000000	0.780488	0.876712	0.890244	0.036
7	Random Forest	Fold 8	21	219	0	10	0.677419	1.000000	0.000000	0.322581	0.952	1.000000	0.677419	0.807692	0.838710	0.048
8	Random Forest	Fold 9	30	212	0	8	0.789474	1.000000	0.000000	0.210526	0.968	1.000000	0.789474	0.882353	0.894737	0.032
9	Random Forest	Fold 10	28	215	0	7	0.800000	1.000000	0.000000	0.200000	0.972	1.000000	0.800000	0.888889	0.900000	0.028
10	SVM	Fold 1	26	220	0	4	0.866667	1.000000	0.000000	0.133333	0.984	1.000000	0.866667	0.928571	0.933333	0.016
11	SVM	Fold 2	25	221	0	4	0.862069	1.000000	0.000000	0.137931	0.984	1.000000	0.862069	0.925926	0.931034	0.016
12	SVM	Fold 3	24	220	0	6	0.800000	1.000000	0.000000	0.200000	0.976	1.000000	0.800000	0.888889	0.900000	0.024
13	SVM	Fold 4	16	228	0	6	0.727273	1.000000	0.000000	0.272727	0.976	1.000000	0.727273	0.842105	0.863636	0.024
14	SVM	Fold 5	28	212	0	10	0.736842	1.000000	0.000000	0.263158	0.960	1.000000	0.736842	0.848485	0.868421	0.040
15	SVM	Fold 6	27	214	0	9	0.750000	1.000000	0.000000	0.250000	0.964	1.000000	0.750000	0.857143	0.875000	0.036
16	SVM	Fold 7	32	209	0	9	0.780488	1.000000	0.000000	0.219512	0.964	1.000000	0.780488	0.876712	0.890244	0.036
17	SVM	Fold 8	22	219	0	9	0.709677	1.000000	0.000000	0.290323	0.956	1.000000	0.709677	0.830189	0.854839	0.044
18	SVM	Fold 9	30	211	1	8	0.789474	0.995283	0.004717	0.210526	0.964	0.967742	0.789474	0.869565	0.892378	0.036
19	SVM	Fold 10	29	215	0	6	0.828571	1.000000	0.000000	0.171429	0.976	1.000000	0.828571	0.906250	0.914286	0.024
20	LSTM	Fold 1	26	219	1	4	0.866667	0.995455	0.004545	0.133333	0.980	0.962963	0.866667	0.912281	0.931061	0.020
21	LSTM	Fold 2	27	221	0	2	0.931034	1.000000	0.000000	0.068966	0.992	1.000000	0.931034	0.964286	0.965517	0.008
22	LSTM	Fold 3	25	219	1	5	0.833333	0.995455	0.004545	0.166667	0.976	0.961538	0.833333	0.892857	0.914394	0.024
23	LSTM	Fold 4	19	228	0	3	0.863636	1.000000	0.000000	0.136364	0.988	1.000000	0.863636	0.926829	0.931818	0.012
24	LSTM	Fold 5	30	212	0	8	0.789474	1.000000	0.000000	0.210526	0.968	1.000000	0.789474	0.882353	0.894737	0.032
25	LSTM	Fold 6	31	212	2	5	0.861111	0.990654	0.009346	0.138889	0.972	0.939394	0.861111	0.898551	0.925883	0.028
26	LSTM	Fold 7	36	207	2	5	0.878049	0.990431	0.009569	0.121951	0.972	0.947368	0.878049	0.911392	0.934240	0.028
27	LSTM	Fold 8	25	216	3	6	0.806452	0.986301	0.013699	0.193548	0.964	0.892857	0.806452	0.847458	0.896376	0.036
28	LSTM	Fold 9	32	211	1	6	0.842105	0.995283	0.004717	0.157895	0.972	0.969697	0.842105	0.901408	0.918694	0.028
29	LSTM	Fold 10	31	215	0	4	0.885714	1.000000	0.000000	0.114286	0.984	1.000000	0.885714	0.939394	0.942857	0.016

	Brier
0	0.024
1	0.028
2	0.024
3	0.020

4	0.289474	0.956	1.000000	0.710526	0.830769	0.855263	0.044
5	0.250000	0.960	0.964286	0.750000	0.843750	0.872664	0.040
6	0.219512	0.964	1.000000	0.780488	0.876712	0.890244	0.036
7	0.322581	0.960	1.000000	0.677419	0.807692	0.838710	0.040
8	0.210526	0.968	1.000000	0.789474	0.882353	0.894737	0.032
9	0.200000	0.972	1.000000	0.800000	0.888889	0.900000	0.028
10	0.133333	0.984	1.000000	0.866667	0.928571	0.933333	0.016
11	0.137931	0.984	1.000000	0.862069	0.925926	0.931034	0.016
12	0.200000	0.976	1.000000	0.800000	0.888889	0.900000	0.024
13	0.272727	0.976	1.000000	0.727273	0.842105	0.863636	0.024
14	0.263158	0.960	1.000000	0.736842	0.848485	0.868421	0.040
15	0.250000	0.964	1.000000	0.750000	0.857143	0.875000	0.036
16	0.219512	0.964	1.000000	0.780488	0.876712	0.890244	0.036
17	0.290323	0.964	1.000000	0.709677	0.830189	0.854839	0.036
18	0.210526	0.964	0.967742	0.789474	0.869565	0.892378	0.036
19	0.171429	0.976	1.000000	0.828571	0.906250	0.914286	0.024
20	0.133333	0.980	0.962963	0.866667	0.912281	0.931061	0.020
21	0.068966	0.992	1.000000	0.931034	0.964286	0.965517	0.008
22	0.166667	0.976	0.961538	0.833333	0.892857	0.914394	0.024
23	0.136364	0.988	1.000000	0.863636	0.926829	0.931818	0.012
24	0.210526	0.968	1.000000	0.789474	0.882353	0.894737	0.032
25	0.138889	0.972	0.939394	0.861111	0.898551	0.925883	0.028
26	0.121951	0.972	0.947368	0.878049	0.911392	0.934240	0.028
27	0.193548	0.964	0.892857	0.806452	0.847458	0.896376	0.036
28	0.157895	0.972	0.969697	0.842105	0.901408	0.918694	0.028
29	0.114286	0.984	1.000000	0.885714	0.939394	0.942857	0.016

	Brier Skill Score
0	0.227273
1	0.273054
2	0.227273
3	0.249203
4	0.341360
5	0.324507
6	0.262574
7	0.368243
8	0.248262
9	0.232558
10	0.151515
11	0.156031
12	0.227273
13	0.299043
14	0.310328
15	0.292056
16	0.262574
17	0.331418
18	0.279295

```
19          0.199336
20          0.189394
21          0.078015
22          0.227273
23          0.149522
24          0.248262
25          0.227155
26          0.204225
27          0.331418
28          0.217229
29          0.132890
```

[113]:
```
all_metrics.shape
```

[113]:
```
(30, 17)
```

5.15 Calculate Mean

[114]:
```
all_metrics.drop('Fold', axis=1).groupby('ModelName').mean()
```

[114]:
```
                  TP     TN   FP   FN       TPR       TNR       FPR       FNR  \
ModelName
LSTM            28.2  216.0  1.0  4.8  0.855758  0.995358  0.004642  0.144242
Random Forest   25.3  216.8  0.2  7.7  0.767259  0.999078  0.000922  0.232741
SVM             25.9  216.9  0.1  7.1  0.785106  0.999528  0.000472  0.214894

                Accuracy  Precision    Recall        F1       AUC   Brier  \
ModelName
LSTM              0.9768   0.967382  0.855758  0.907681  0.925558  0.0232
Random Forest     0.9684   0.992582  0.767259  0.864645  0.883169  0.0316
SVM               0.9712   0.996774  0.785106  0.877384  0.892317  0.0288

                Brier Skill Score
ModelName
LSTM                     0.200538
Random Forest            0.275431
SVM                      0.250887
```

5.15.1 Print in terminal

[115]:
```
# print in terminal
def print_all_metrics(all_metrics):
    mean_df = all_metrics.drop('Fold', axis=1).groupby('ModelName').mean()
    for col in mean_df.columns:
        print(f"Mean {col} for each model")
        print(mean_df[col])
        print("\n")
print("-"*30)
```

```
print("Mean of Metrics for each model")
print("-"*30)
print_all_metrics(all_metrics)
print("-"*30)
```

```
------------------------------
Mean of Metrics for each model
------------------------------
Mean TP for each model
ModelName
LSTM             28.2
Random Forest    25.3
SVM              25.9
Name: TP, dtype: float64


Mean TN for each model
ModelName
LSTM             216.0
Random Forest    216.8
SVM              216.9
Name: TN, dtype: float64


Mean FP for each model
ModelName
LSTM             1.0
Random Forest    0.2
SVM              0.1
Name: FP, dtype: float64


Mean FN for each model
ModelName
LSTM             4.8
Random Forest    7.7
SVM              7.1
Name: FN, dtype: float64


Mean TPR for each model
ModelName
LSTM             0.855758
Random Forest    0.767259
SVM              0.785106
Name: TPR, dtype: float64
```

```
Mean TNR for each model
ModelName
LSTM             0.995358
Random Forest    0.999078
SVM              0.999528
Name: TNR, dtype: float64


Mean FPR for each model
ModelName
LSTM             0.004642
Random Forest    0.000922
SVM              0.000472
Name: FPR, dtype: float64


Mean FNR for each model
ModelName
LSTM             0.144242
Random Forest    0.232741
SVM              0.214894
Name: FNR, dtype: float64


Mean Accuracy for each model
ModelName
LSTM             0.9768
Random Forest    0.9684
SVM              0.9712
Name: Accuracy, dtype: float64


Mean Precision for each model
ModelName
LSTM             0.967382
Random Forest    0.992582
SVM              0.996774
Name: Precision, dtype: float64


Mean Recall for each model
ModelName
LSTM             0.855758
Random Forest    0.767259
SVM              0.785106
Name: Recall, dtype: float64
```

```
Mean F1 for each model
ModelName
LSTM              0.907681
Random Forest     0.864645
SVM               0.877384
Name: F1, dtype: float64


Mean AUC for each model
ModelName
LSTM              0.925558
Random Forest     0.883169
SVM               0.892317
Name: AUC, dtype: float64


Mean Brier for each model
ModelName
LSTM              0.0232
Random Forest     0.0316
SVM               0.0288
Name: Brier, dtype: float64


Mean Brier Skill Score for each model
ModelName
LSTM              0.200538
Random Forest     0.275431
SVM               0.250887
Name: Brier Skill Score, dtype: float64


------------------------------
```

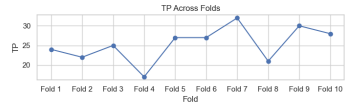
6 Visualization

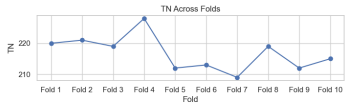
6.1 Plot all metrics of Random Forest Classifier for each fold

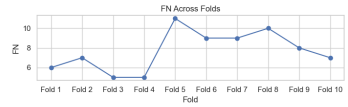
[116]:
```
rf_metrics_df_plot = pd.DataFrame(rf_metrics, columns=columns)
rf_metrics_df_plot.drop('Fold', axis=1, inplace=True)
# List of metrics to plot
metrics = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR', 'FNR', 'Accuracy',␣
 ↪'Precision', 'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']

# Plotting the metrics for each fold
fig, axes = plt.subplots(len(metrics), 1, figsize=(8, 40))
fig.suptitle('Random Forest Metrics Across Folds', fontsize=16)
```

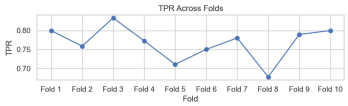
```
for i, metric in enumerate(metrics):
    axes[i].plot(rf_metrics_df['Fold'], rf_metrics_df[metric], marker='o')
    axes[i].set_title(f'{metric} Across Folds')
    axes[i].set_xlabel('Fold')
    axes[i].set_ylabel(metric)
    axes[i].grid(True)

plt.tight_layout(rect=[0, 0, 1, 0.97])
plt.show()
```

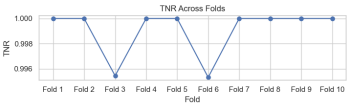
Random Forest Metrics Across Folds

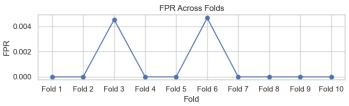


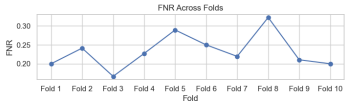


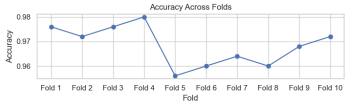


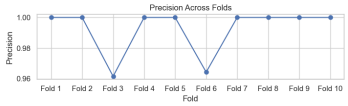


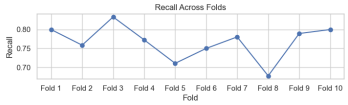


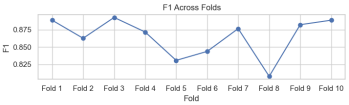


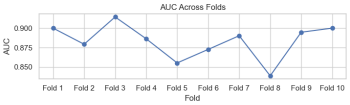


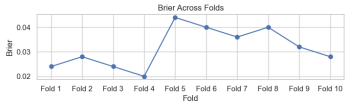


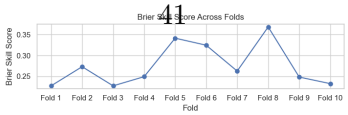








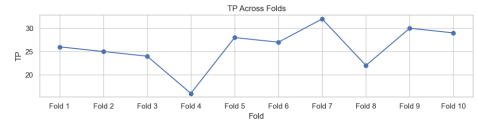


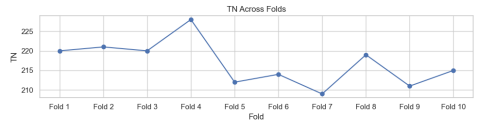


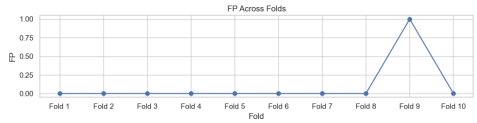
6.2 Plot all metrics of SVM for each fold

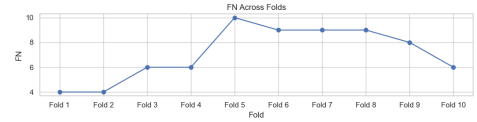
[117]:
```
import matplotlib.pyplot as plt

svm_metrics_df_plot = pd.DataFrame(svm_metrics, columns=columns)
svm_metrics_df_plot.drop('Fold', axis=1, inplace=True)
# List of metrics to plot
metrics = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR', 'FNR', 'Accuracy',␣
 ↪'Precision', 'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']

# Plotting the metrics for each fold
fig, axes = plt.subplots(len(metrics), 1, figsize=(10, 40))
fig.suptitle('SVM Metrics Across Folds', fontsize=16)

for i, metric in enumerate(metrics):
    axes[i].plot(svm_metrics_df['Fold'], svm_metrics_df[metric], marker='o')
    axes[i].set_title(f'{metric} Across Folds')
    axes[i].set_xlabel('Fold')
    axes[i].set_ylabel(metric)
    axes[i].grid(True)

plt.tight_layout(rect=[0, 0, 1, 0.97])
plt.show()
```

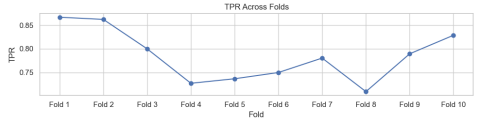
SVM Metrics Across Folds

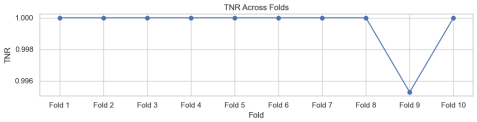


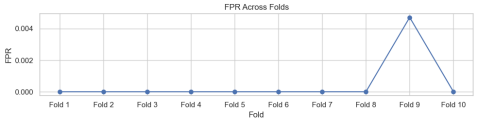


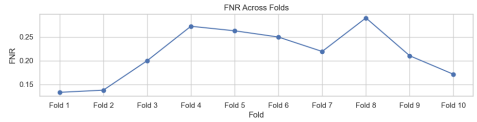


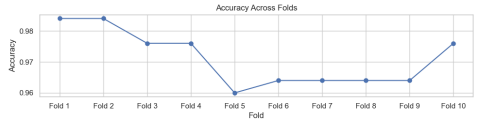


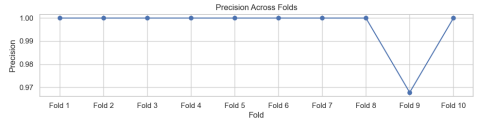


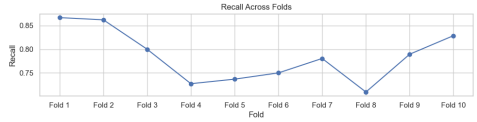


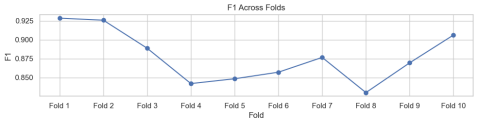


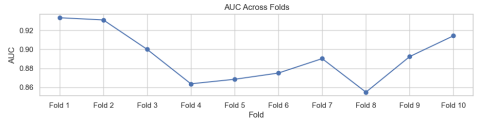


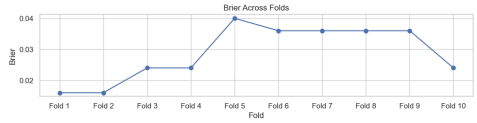


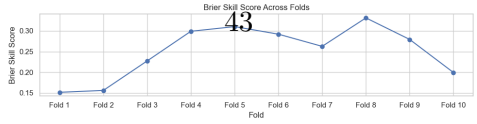








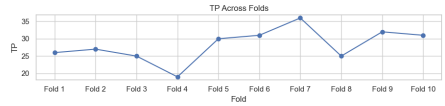


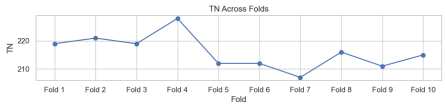


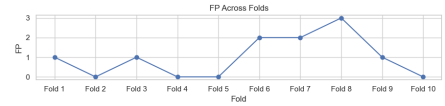
6.3 Plot all metrics of LSTM for each fold

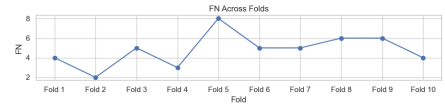
[118]:
```
lstm_metrics_df_plot = pd.DataFrame(lstm_metrics, columns=columns)
lstm_metrics_df_plot.drop('Fold', axis=1, inplace=True)
# List of metrics to plot
metrics = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR', 'FNR', 'Accuracy',␣
 ↪'Precision', 'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']

# Plotting the metrics for each fold
fig, axes = plt.subplots(len(metrics), 1, figsize=(10, 40))
fig.suptitle('LSTM Metrics Across Folds', fontsize=16)

for i, metric in enumerate(metrics):
    axes[i].plot(lstm_metrics_df['Fold'], lstm_metrics_df[metric], marker='o')
    axes[i].set_title(f'{metric} Across Folds')
    axes[i].set_xlabel('Fold')
    axes[i].set_ylabel(metric)
    axes[i].grid(True)

plt.tight_layout(rect=[0, 0, 1, 0.97], pad=3.0)
plt.show()
```

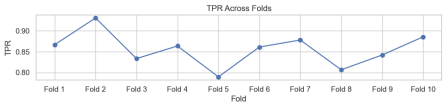
LSTM Metrics Across Folds

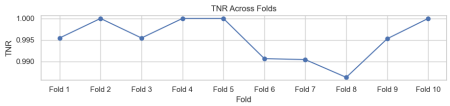


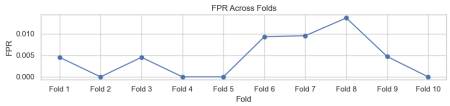


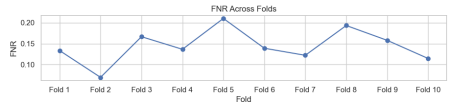


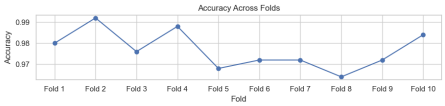


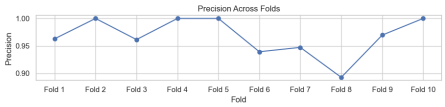


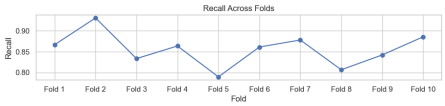


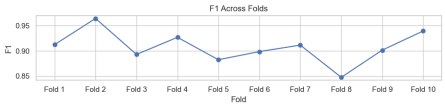


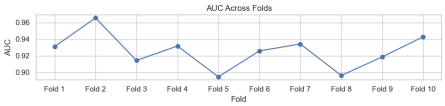


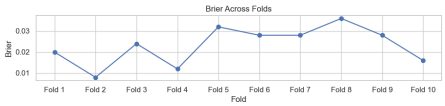


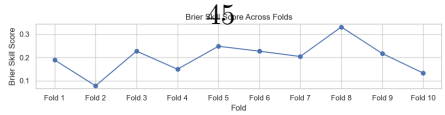






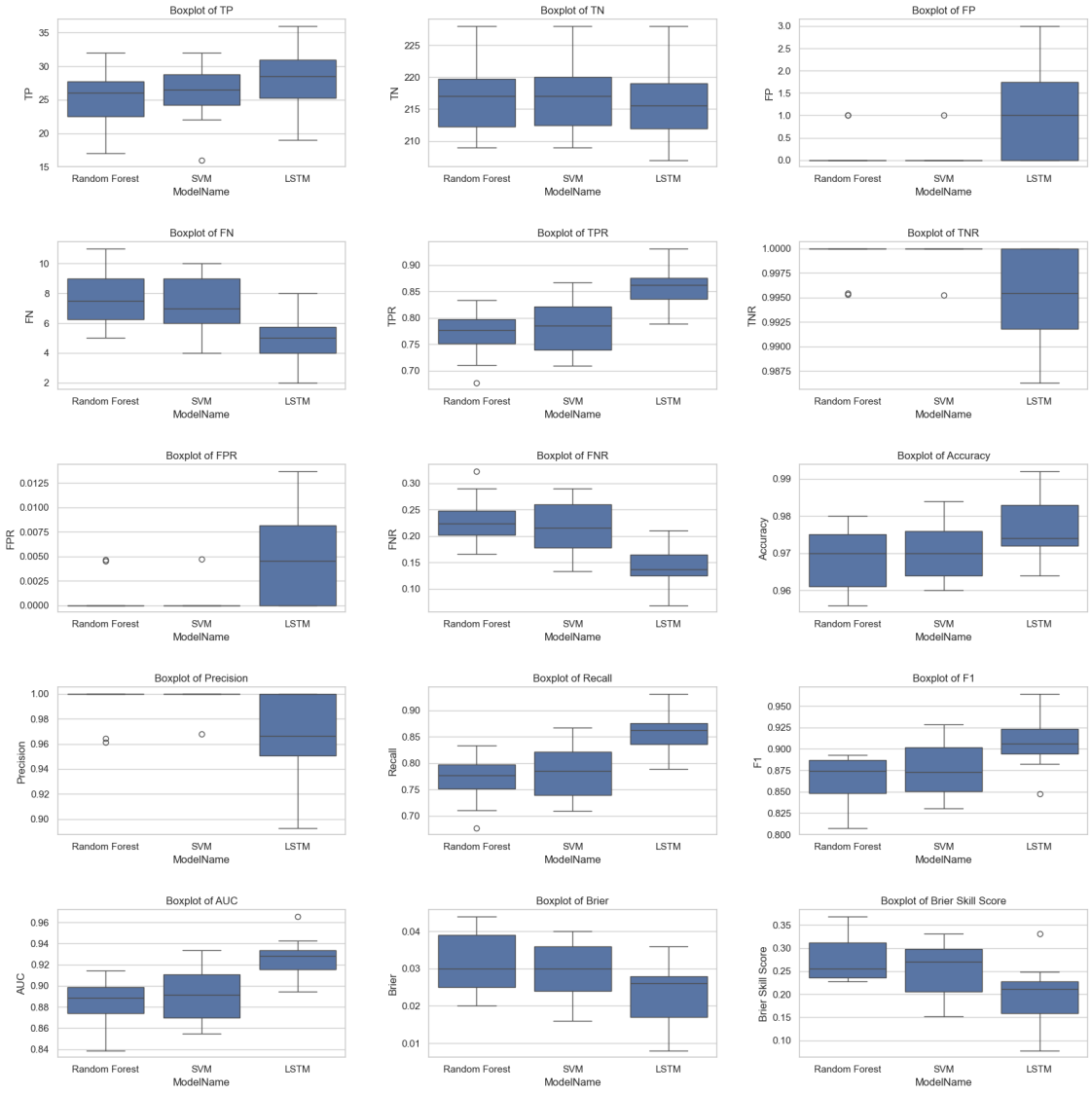






6.4 BoxPlot to compare models

[146]:
```
sns.set_theme(style="whitegrid")

# List of metrics to plot
metrics = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR', 'FNR', 'Accuracy',␣
 ↪'Precision',
           'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']

fig, axes = plt.subplots(5, 3, figsize=(18,18))
axes = axes.flatten()

for i, metric in enumerate(metrics):
    sns.boxplot(x='ModelName', y=metric, data=all_metrics, ax=axes[i])
    axes[i].set_title(f'Boxplot of {metric}')

# Adjust the layout
plt.tight_layout(pad=3.0)
plt.show()
```



7 Observation

1. **True Positive (TP)**: LSTM has got more TP for one of the fold than RandomForest and SVM.
2. **True Negative (NP)**: All the 3 models have somewhat similar number of TNs.
3. **False Positives (FP)**: RF and SVM have lowest count of FP compared to LSTM which shows some variation. We can also observe that there are some outliers in this case for RF and SVM.
4. **False Negatives (FN)**: RF and SVM have slightly higher number of FNs than LSTM
5. **True Positive Rate (TPR)**: LSTM has a higher TPR compared to RF and SVM, indicating better sensitivity.
6. **True Negative Rate (TNR)**: All models have similar TNR, with LSTM showing slightly

more variation.

7. **False Positive Rate (FPR)**: RF and SVM have lower FPR compared to LSTM, indicating fewer false alarms.
8. **False Negative Rate (FNR)**: LSTM has a lower FNR compared to RF and SVM, indicating fewer missed detections.
9. **Accuracy**: LSTM shows higher accuracy across folds compared to RF and SVM.
10. **Precision**: All the models have similar precision, with LSTM showing slightly higher variation.
11. **Recall**: LSTM has higher recall, indicating better sensitivity.
12. **F1 Score**: LSTM has a higher F1 score, indicating a better balance between precision and recall.
13. **AUC**: LSTM has a higher AUC, indicating better overall performance.
14. **Brier Score**: LSTM has a lower Brier score, indicating better probabilistic predictions.
15. **Brier Skill Score**: LSTM has a lower Brier Skill Score, indicating better probabilistic predictions.

8 Discussion

Based on the observations we can say that the LSTM model performs better than the Random Forest and SVM models in a number of important metrics. Overall accuracy, precision, recall, and F1 score are all higher for the LSTM model, along with a reduced False Negative Rate (FNR) and a higher True Positive Rate (TPR). This suggests that the LSTM model minimizes false negatives while improving the accuracy of spam message identification.

Additionally, the LSTM model's AUC (Area Under the Curve) score is higher, indicating that it performs better overall in differentiating between spam and ham messages. Furthermore, the LSTM model's lower Brier score suggests that its probabilistic predictions are more accurate.

It's crucial to remember that the Random Forest and SVM models still have their own benefits and function very effectively. For example, they are less likely to mistakenly identify ham transmissions as spam due to their reduced False Positive Rates (FPR) and they are faster to compute than LSTM models.

9 Conclusion

By evaluating the metrics we can conclude that LSTM outperforms Random Forest and SVM in terms of classification accuracy and other important assessment criteria. However, LSTMs are more complex than Random Forest and SVMs to train. On the other hand, Random Forest and SVM provide consistent performance with a much easier implementation, which makes them the best options when model stability, usability, and quicker training times are more important than optimal performance.

10 Github Repository Link

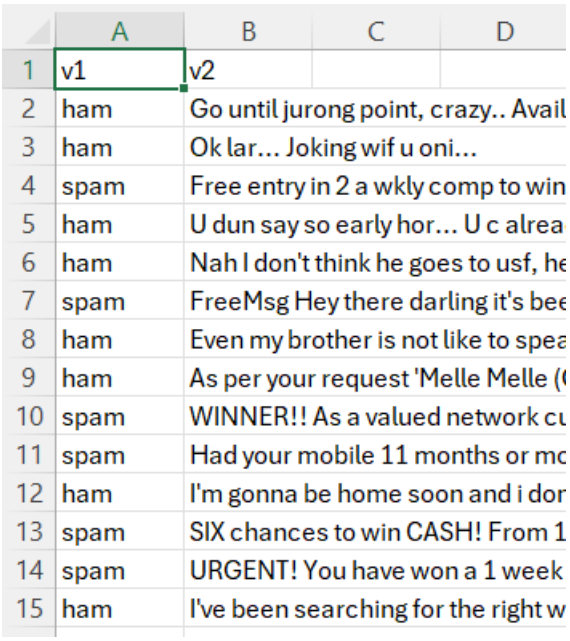
jd849@njit.edu -> Github Repository Link

11 Screenshots of implementation

The below image shows a sample of our dataset

[120]:
```
Image("ss/6.png")
```

[120]:



	A	B	C	D
1	v1	v2		
2	ham	Go until jurong point, crazy.. Avail		
3	ham	Ok lar... Joking wif u oni...		
4	spam	Free entry in 2 a wkly comp to win		
5	ham	U dun say so early hor... U c alrea		
6	ham	Nah I don't think he goes to usf, he		
7	spam	FreeMsg Hey there darling it's bee		
8	ham	Even my brother is not like to spea		
9	ham	As per your request 'Melle Melle ((		
10	spam	WINNER!! As a valued network cu		
11	spam	Had your mobile 11 months or mo		
12	ham	I'm gonna be home soon and i dor		
13	spam	SIX chances to win CASH! From 1		
14	spam	URGENT! You have won a 1 week		
15	ham	I've been searching for the right w		

First we load the dataset into a pandas dataframe

[121]:
```
Image("ss/7.png")
```

[121]:

Load Dataset

- Loading the dataset to our pandas dataframe
- The dataset consists of 2 main columns: Messages and Category
- Message: Contains the data or text of our message
- Category: Specifies if the message is a spam or a ham

[407]:
```
df = pd.read_csv("spam.csv", encoding="latin-1")
df.head()
```

[407]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only ...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro...	NaN	NaN	NaN

[408]:
```
df.columns
```

[408]:
```
Index(['v1', 'v2', 'Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], dtype='object')
```

Now we preprocess the dataset columns by pruning redundant columns and renmaing the useful columns to something more comprehnsible

[122]:
```
Image("ss/8.png")
```

[122]:

Preprocess Columns

```
[409]: cols_to_drop = ["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"]
       df = df.drop(cols_to_drop, axis=1)
```

```
[410]: df.columns = ["Category", "Message"]
```

```
[411]: df.head()
```

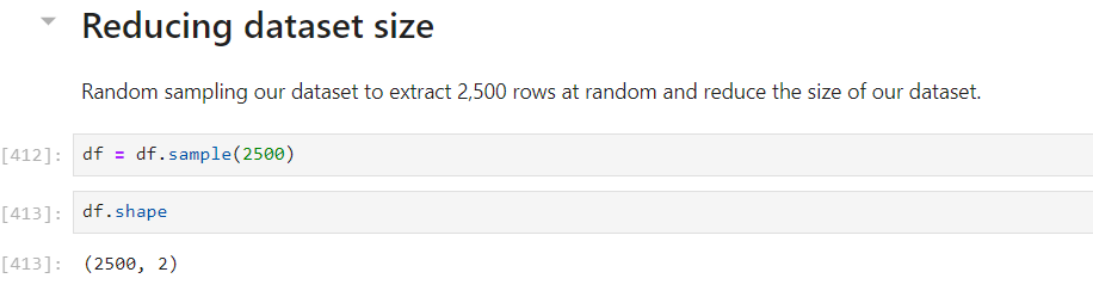
[411]:

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

Now we reduce the size of our dataset to 2,500 Rows by using random sampling. This reduces the amount of data that the models will train on, which in turn reduces the training time.

```
[123]: Image("ss/9.png")
```

[123]:



Reducing dataset size

Random sampling our dataset to extract 2,500 rows at random and reduce the size of our dataset.

```
[412]: df = df.sample(2500)
```

```
[413]: df.shape
```

```
[413]: (2500, 2)
```

Label Encoding is the step where we encode target variables, which are in textual format (red, blue, green…), and convert them into numerical form (0, 1, 2…). In our case we have only 2 categories in the target variable - **Spam** and **Ham**. So there are only 2 numbers after label encoding - **0** and **1**.

```
[124]: Image("ss/10.png")
```

[124]:

Label Encoding

Converting target variable to 0 and 1 instead of the text `ham` and `spam`. Set the target variable to 1 if the category is "spam" and 0 if the category is "ham"

[414]:
```
df['spam']=df['Category'].apply(lambda x: 1 if x=='spam' else 0)
df.head()
```

[414]:

	Category	Message	spam
3245	ham	Funny fact Nobody teaches volcanoes 2 erupt, t...	0
944	ham	I sent my scores to sophas and i had to do sec...	0
1044	spam	We know someone who you know that fancies you....	1
2484	ham	Only if you promise your getting out as SOON a...	0
812	spam	Congratulations ur awarded either å£500 of CD ...	1

[415]:
```
df.sample(1)
```

[415]:

	Category	Message	spam
1556	ham	Good sleep is about rhythm. The person has to ...	0

Now we preprocess the dataset for our Machine Learning algorithms * We use count vectorizer which converts texts to a matrix of token count. * This is done because ML models do not train on text data but rather the numerical format of the text data.

[125]:
```
Image("ss/11.png")
```

[125]:

Preprocess - For ML

Count Vectorizer

Count Vectorizer converts a collection of text documents (a dataframe of rows in our case) to a matrix of token count.

[416]:
```
cv = CountVectorizer()
X_cv = cv.fit_transform(df['Message'])
y = df['spam']
```

Now we define functions to calculate the the metrics. The functions defined are: 1. **create_cm** - This function creates and returns a confusion matrix of the **tp, tn, fp and fn**. 2. **calc_bss** - This function is used to calculate and return the **Brier Skill Score**. 3. **calc_all_metrics** - This function is used to calculate and return all the metrics of the dataset. The functions **create_cm** and **calc_bss** are called over here. This function then returns the array of all the metrics that are calculated. All the metrics calculated are: * TP - Number of True Positives * FP - Number of False Positives * TN - Number of True Negatives * FN - Number of False Negatives * TPR - True Positive Rate * FPR - False Positive Rate * TNR - True Negative Rate * FNR - False Negative Rate * Accuracy Score * Precision Score * Recall Score * F1 Score * Brier Score * ROC AUC Score * BSS - Brier Skill Score

[126]:
```
Image("ss/12.png")
```

[126]:

Functions to Calculate Metrics

Function to create the confusion matrix

[417]:
```
def create_cm(tp, tn, fp, fn):
    cm = np.array([[tp, fp], [fn, tn]])
    return cm
```

Function to calculate Brier Skill Score (BSS)

[418]:
```
def calc_bss(y_test, bs):
    mean = np.mean(y_test)
    brier_ref = np.mean((y_test - mean) ** 2)
    bss = bs/brier_ref
    return bss
```

[127]:
```
Image("ss/13.png")
```

[127]:

Function to calculate all metrics ¶

[419]:
```
def calc_all_metrics(y_test, y_pred, i):
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()

    # Rate
    tpr = tp / (tp + fn)
    tnr = tn / (tn + fp)
    fpr = fp / (fp + tn)
    fnr = fn / (fn + tp)

    accuracy = (tp + tn) / (tp + tn + fp + fn)
    precision = tp / (tp + fp)
    recall = tp / (tp + fn)
    f1 = (2 * precision * recall) / (precision + recall)

    auc_score = roc_auc_score(y_test, y_pred)

    brier = brier_score_loss(y_test, y_pred)
    brier_skill_score = calc_bss(y_test, brier)

    cm = create_cm(tp, tn, fp, fn)

    print("Metrics for Fold ", i)
    print("-"*10)
    print("Confusion Matrix for Fold ", i)
    print(cm)
    print("Number of True Positives ", tp)
    print("Number of False Positives ", fp)
```

The plotting function is defined to plot the AUC-ROC curve for each fold of the model.

[128]:
```
Image("ss/14.png")
```

[128]:

Plotting Function ¶

Function to plot the AUC-ROC Curve for each fold of the model

[420]:
```
def plot_roc_curves_in_grid(roc_data, model_name):
    n_rows = int(np.ceil(len(roc_data) / 3))
    fig, axes = plt.subplots(n_rows, 3, figsize=(10, n_rows * 3))
    axes = axes.flatten()  # Flatten the axes to make indexing easier

    for i, (fpr, tpr, auc_score) in enumerate(roc_data):
        ax = axes[i]
        ax.plot(fpr, tpr, label=f"ROC Curve (AUC) score {auc_score:.2f}")
        ax.plot([0, 1], [0, 1], linestyle='--')  # Diagonal line (random classifier)
        ax.set_xlabel('False Positive Rate')
        ax.set_ylabel('True Positive Rate')
        ax.set_title(f'{model_name} Fold {i + 1} ROC Curve')

    for j in range(i + 1, len(axes)):
        axes[j].axis('off')

    plt.tight_layout(pad=3.0)
    plt.show()
```

The dataset is divided into 10 equal parts (called folds), where each fold is used once as a test set while the remaining 9 folds are used as the training set. This is achieved using KFold from sklearn.model_selection.

[129]:
```
Image("ss/15.png")
```

[129]:

Creating 10-Fold

The dataset is divided into 10 equal parts (called folds), where each fold is used once as a test set while the remaining 9 folds are used as the training set.

[421]:
```
N_SPLITS = 10
kf = KFold(n_splits=N_SPLITS, shuffle=True, random_state=42)
```

The Random Forest Classifier is trained on the dataset and the metrics are calculated for each fold. The metrics are then stored in a pandas dataframe.

[130]:
```
Image("ss/16.png")
```

[130]:

Random Forest Classifier

[422]:
```
rf_metrics = []
rf_roc_data = []

print("-"*20)
print("Starting Random Forest Training")
print("-"*20)

# Loop through the 10Fold splits
for i, (train_index, test_index) in enumerate(kf.split(X_cv), start=1):
    # Splitting the data into train and test split
    X_train, X_test = X_cv[train_index], X_cv[test_index] # type: ignore
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    print(f"Training Fold {i}")

    # Training the model
    rf = RandomForestClassifier()
    rf.fit(X_train, y_train)
    y_pred = rf.predict(X_test)

    # Calculating the AUC-ROC curve and score
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    auc_score = roc_auc_score(y_test, y_pred)
    rf_roc_data.append((fpr, tpr, auc_score))

    # Calculate all the metrics and store them
    rf_metrics.append(calc_all_metrics(y_test, y_pred, i))
```

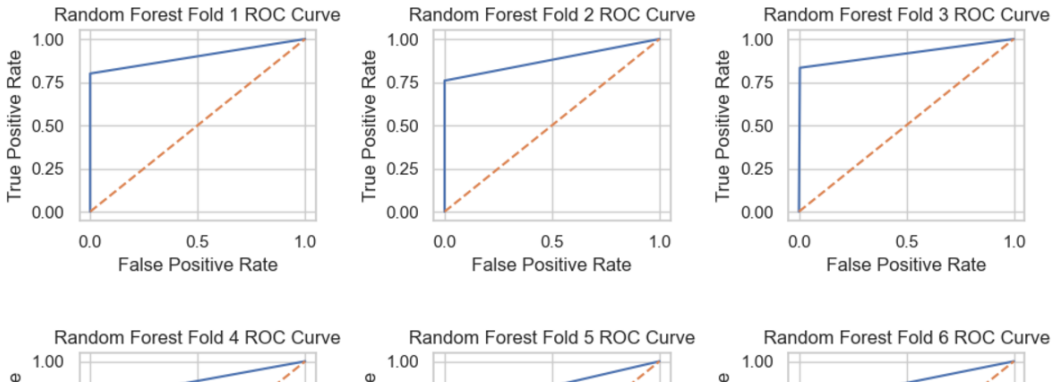
- Once the Random Forest Classifier is trained, we add the name of the model to the metrics to later differentiate between the models when stored in the dataframe.
- We also call the plotting function to plot the AUC-ROC curve for each fold of the model based on the metrics calculated.

[131]:
```
Image("ss/17.png")
```

[131]:

[423]:
```
# Add model name to column
for i, metric in enumerate(rf_metrics):
    metric.insert(0, 'Random Forest')
```

[424]:
```
plot_roc_curves_in_grid(rf_roc_data, "Random Forest")
```



Now we train the SVM model. SVM is trained on the dataset and the metrics are calculated for

each fold. The metrics are then stored in an array which is later used to create a dataframe and tabulate our results.

[132]:
```
Image("ss/18.png")
```

[132]:

SVM

[425]:
```
svm_metrics = []
svm_roc_data = []

print("-"*20)
print("Starting SVM Training")
print("-"*20)

# Loop through the KFold splits
for i, (train_index, test_index) in enumerate(kf.split(X_cv), start=1):
    # Splitting the data into train and test split
    X_train, X_test = X_cv[train_index], X_cv[test_index] # type: ignore
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    print(f"Training Fold {i}! ", end='')
    # Training the model
    svm = SVC()
    svm.fit(X_train, y_train)
    y_pred = svm.predict(X_test)

    # Calculating the AUC-ROC curve and score
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    auc_score = roc_auc_score(y_test, y_pred)
    svm_roc_data.append((fpr, tpr, auc_score))

    # Calculate metrics and storing them
    svm_metrics.append(calc_all_metrics(y_test, y_pred, i))
```

Then we follow the same steps for SVM model as we did for Random Forest Classifier. We add the name of the model to the metrics to later differentiate between the models when stored in the dataframe. We also call the plotting function to plot the AUC-ROC curve for each fold of the model based on the metrics calculated.

[133]:
```
Image("ss/19.png")
```

[133]:

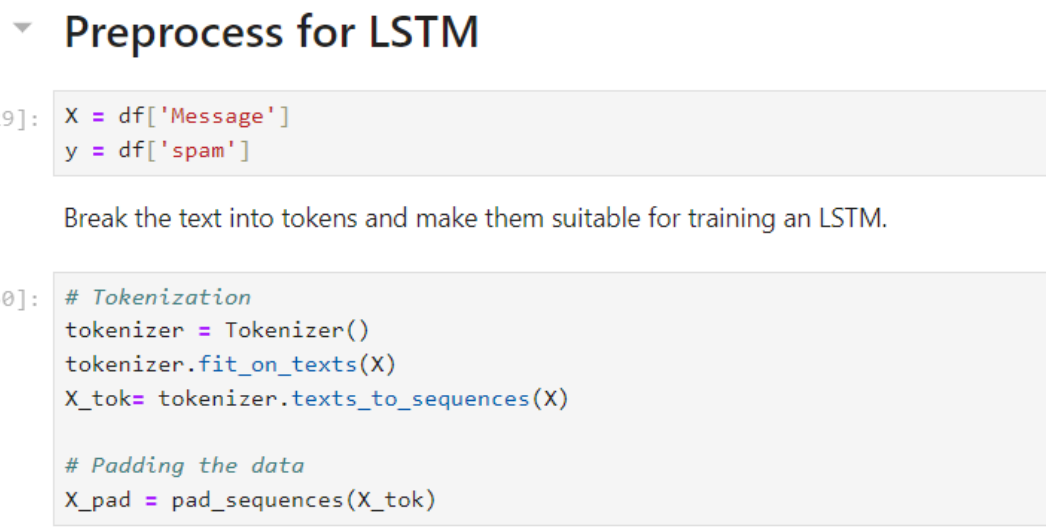
[426]:
```
# add the model name to the metrics
for i, metric in enumerate(svm_metrics):
    metric.insert(0, 'SVM')
```

[427]:
```
plot_roc_curves_in_grid(svm_roc_data, "SVM")
```

- Now we preprocess the dataset for LSTM. We break the text into tokens and make them suitable for training an LSTM.
- We use Tokenizer from `keras.preprocessing.text` to convert the text into tokens.
- We use pad_sequences from `keras.preprocessing.sequence` to pad the sequences to the equal length.

[134]:
```
Image("ss/20.png")
```

[134]:



Preprocess for LSTM

[429]:
```
X = df['Message']
y = df['spam']
```

Break the text into tokens and make them suitable for training an LSTM.

[430]:
```
# Tokenization
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X)
X_tok= tokenizer.texts_to_sequences(X)

# Padding the data
X_pad = pad_sequences(X_tok)
```

Now we definte a function to build the LSTM model. The function is defined as follows: * The function takes in the input and we define the input_shape from the input. This is binary classification so the output contains only 1 neuron which will output - 0 or 1. * The function then builds the LSTM model using the Sequential API from Keras. * The model consists of an Embedding layer, LSTM layer, Dense layer and an output layer. * The model is then compiled using the Adam optimizer and binary crossentropy loss function.

[135]:
```
Image("ss/21.png")
```

[135]:

LSTM

Function to build LSTM model

[428]:
```
def build_model(X_train_pad):
    # Training the model
    model = Sequential()
    model.add(Embedding(input_dim=len(tokenizer.word_index)+1, output_dim=32))
    model.add(LSTM(32))
    model.add(Dense(1, activation='sigmoid'))
    return model
```

Then we train our LSTM model on the dataset. The model is trained on the dataset and the metrics are calculated for each fold. The metrics are then stored in an array which is later used to create a dataframe and tabulate our results.

[136]:
```
Image("ss/22.png")
```

[136]:

Executing

[431]:
```
lstm_metrics = []
lstm_roc_data = []
print("-"*20)
print("Starting LSTM Training")
print("-"*20)
for i, (train_index, test_index) in enumerate(kf.split(X_pad), start=1):
    # Splitting the data into train and test split
    X_train, X_test = X_pad[train_index], X_pad[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # train the LSTM model
    model = build_model(X_train)

    model.compile(loss='binary_crossentropy', optimizer='adam')

    model.fit(X_train, y_train, epochs=2, batch_size=32, verbose=0)
    y_pred = model.predict(X_test, verbose=0) > 0.5

    # Calculating the AUC-ROC score and curve
    fpr, tpr, _ = roc_curve(y_test, y_pred)
    auc_score = roc_auc_score(y_test, y_pred)
    lstm_roc_data.append((fpr, tpr, auc_score))

    # calculating the metrics and storing them
    lstm_metrics.append(calc_all_metrics(y_test, y_pred, i))
```

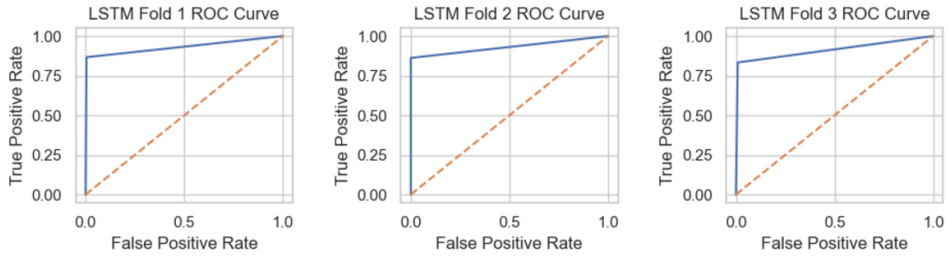
Then we follow the same steps for LSTM model as we did for Random Forest Classifier and SVM. We add the name of the model to the metrics to later differentiate between the models when stored in the dataframe. We also call the plotting function to plot the AUC-ROC curve for each fold of the model based on the metrics calculated.

[137]:
```
Image("ss/23.png")
```

[137]:

[432]:
```
for i, metric in enumerate(lstm_metrics):
    metric.insert(0, 'LSTM')
```

[433]:
```
plot_roc_curves_in_grid(lstm_roc_data, "LSTM")
```



Once all the models are trained and the metrics are calculated, we used the stored metrics data into table format using pandas dataframe. The metrics are stored in the dataframe in the following format: * Fold Number * Model Name * TP * FP * TN * FN * TPR * FPR * TNR * FNR * Accuracy * Precision * Recall * F1 Score * Brier Score * ROC AUC Score * BSS

[138]:
```
Image("ss/24.png")
```

[138]:

Tabulate ¶

Store the data into table format using pandas dataframe

[434]:
```
columns = ['ModelName', 'Fold', 'TP', 'TN', 'FP', 'FN', 'TPR', 'TNR',
           'FPR', 'FNR', 'Accuracy', 'Precision',
           'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']
rf_metrics_df = pd.DataFrame(rf_metrics, columns=columns)
svm_metrics_df = pd.DataFrame(svm_metrics, columns=columns)
lstm_metrics_df = pd.DataFrame(lstm_metrics, columns=columns)
```

Metrics in Table Format

Random Forest Classifier

[435]:
```
rf_metrics_df
```

[435]:

	ModelName	Fold	TP	TN	FP	FN	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F1	AUC	Brier	Brier Skill Score
0	Random Forest	Fold 1	24	220	0	6	0.800000	1.000000	0.000000	0.200000	0.976	1.000000	0.800000	0.888889	0.900000	0.024	0.227273
1	Random Forest	Fold 2	22	221	0	7	0.758621	1.000000	0.000000	0.241379	0.972	1.000000	0.758621	0.862745	0.879310	0.028	0.273054
2	Random Forest	Fold 3	25	219	1	5	0.833333	0.995455	0.004545	0.166667	0.976	0.961538	0.833333	0.892857	0.914394	0.024	0.227273
3	Random Forest	Fold 4	17	228	0	5	0.772727	1.000000	0.000000	0.227273	0.980	1.000000	0.772727	0.871795	0.886364	0.020	0.249203

We then group the metrics by their ModelName and calculate the mean of all the metrics in the dataframe. This gives us an average performance of the model across all the folds.

[139]:
```
Image("ss/25.png")
```

[139]:

Calculate Mean

Calculate mean of all the metrics in the dataframe and group them by their ModelName

```
[440]: all_metrics.drop('Fold', axis=1).groupby('ModelName').mean()
```

[440]:

ModelName	TP	TN	FP	FN	TPR	TNR	FPR	FNR	Accuracy	Precision	Recall	F1	AUC	Brier	Brier Skill Score
LSTM	28.0	215.9	1.1	5.0	0.847491	0.994930	0.005070	0.152509	0.9756	0.963068	0.847491	0.900901	0.921210	0.0244	0.214292
Random Forest	25.3	216.8	0.2	7.7	0.767259	0.999078	0.000922	0.232741	0.9684	0.992582	0.767259	0.864645	0.883169	0.0316	0.275431
SVM	25.9	216.9	0.1	7.1	0.785106	0.999528	0.000472	0.214894	0.9712	0.996774	0.785106	0.877384	0.892317	0.0288	0.250887

Function print_all_metrics is used to print the mean of all metrics for each model in the dataframe.

```
[140]: Image("ss/26.png")
```

[140]:

```
[441]: # print in terminal
def print_all_metrics(all_metrics):
    mean_df = all_metrics.drop('Fold', axis=1).groupby('ModelName').mean()
    for col in mean_df.columns:
        print(f"Mean {col} for each model")
        print(mean_df[col])
        print("\n")
print("-"*30)
print("Mean of Metrics for each model")
print("-"*30)
print_all_metrics(all_metrics)
print("-"*30)
```

```
------------------------------
Mean of Metrics for each model
------------------------------
Mean TP for each model
ModelName
LSTM              28.0
Random Forest     25.3
SVM               25.9
Name: TP, dtype: float64


Mean TN for each model
ModelName
LSTM              215.9
Random Forest     216.8
SVM               216.9
Name: TN, dtype: float64
```

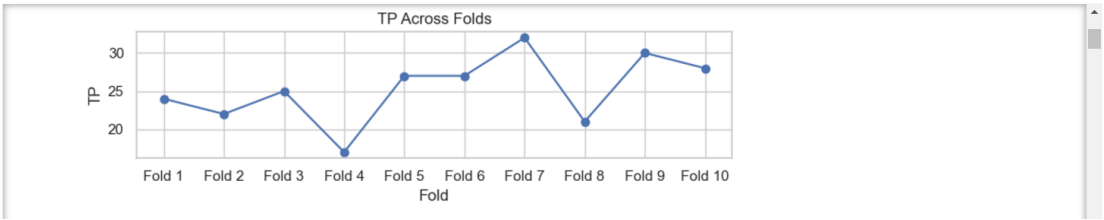
- Now we plot the metrics of Random Forest Classifier by their each folds. The metrics are plotted in the form of a line graph.
- This is done to visualize the performance of the model across all the folds.
- This is also done for SVM and LSTM models.

```
[141]: Image("ss/27.png")
```

[141]:

Plot all metrics of Random Forest Classifier for each fold ¶

[442]:
```
rf_metrics_df_plot = pd.DataFrame(rf_metrics, columns=columns)
rf_metrics_df_plot.drop('Fold', axis=1, inplace=True)
# List of metrics to plot
metrics = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR', 'FNR', 'Accuracy', 'Precision', 'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']

# Plotting the metrics for each fold
fig, axes = plt.subplots(len(metrics), 1, figsize=(8, 40))
fig.suptitle('Random Forest Metrics Across Folds', fontsize=16)

for i, metric in enumerate(metrics):
    axes[i].plot(rf_metrics_df['Fold'], rf_metrics_df[metric], marker='o')
    axes[i].set_title(f'{metric} Across Folds')
    axes[i].set_xlabel('Fold')
    axes[i].set_ylabel(metric)
    axes[i].grid(True)

plt.tight_layout(rect=[0, 0, 1, 0.97], pad=3.0)
plt.show()
```



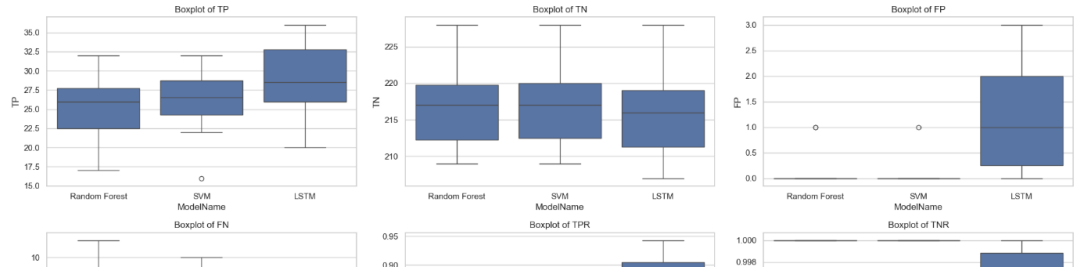
Finally, we plot a boxplot to compare the performance of all the models, giving us a highs, lows, outliers, etc. This is done to compare the performance of the models and see which model performs the best.

[142]:
```
Image("ss/28.png")
```

[142]:

BoxPlot to compare models

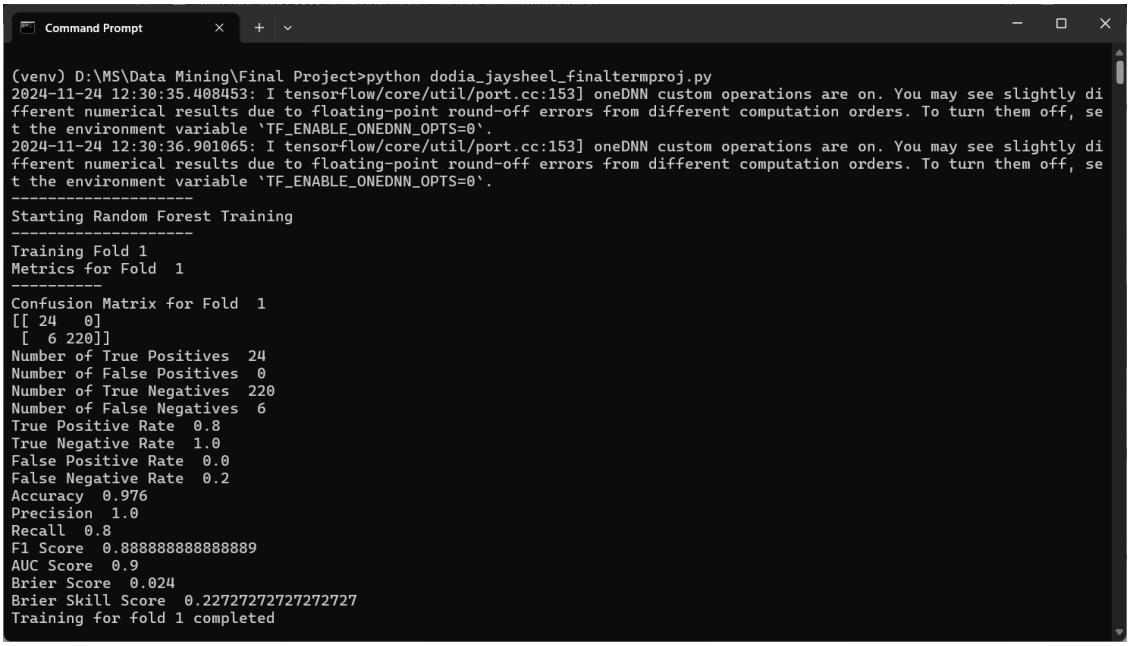
[47]:
```
sns.set_theme(style="whitegrid")

# List of metrics to plot
metrics = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR', 'FNR', 'Accuracy', 'Precision',
           'Recall', 'F1', 'AUC', 'Brier', 'Brier Skill Score']

fig, axes = plt.subplots(5, 3, figsize=(20, 20))
axes = axes.flatten()

for i, metric in enumerate(metrics):
    sns.boxplot(x='ModelName', y=metric, data=all_metrics, ax=axes[i])
    axes[i].set_title(f'Boxplot of {metric}')

# Adjust the layout
plt.tight_layout()
plt.show()
```



12 Python Script Execution Screenshots

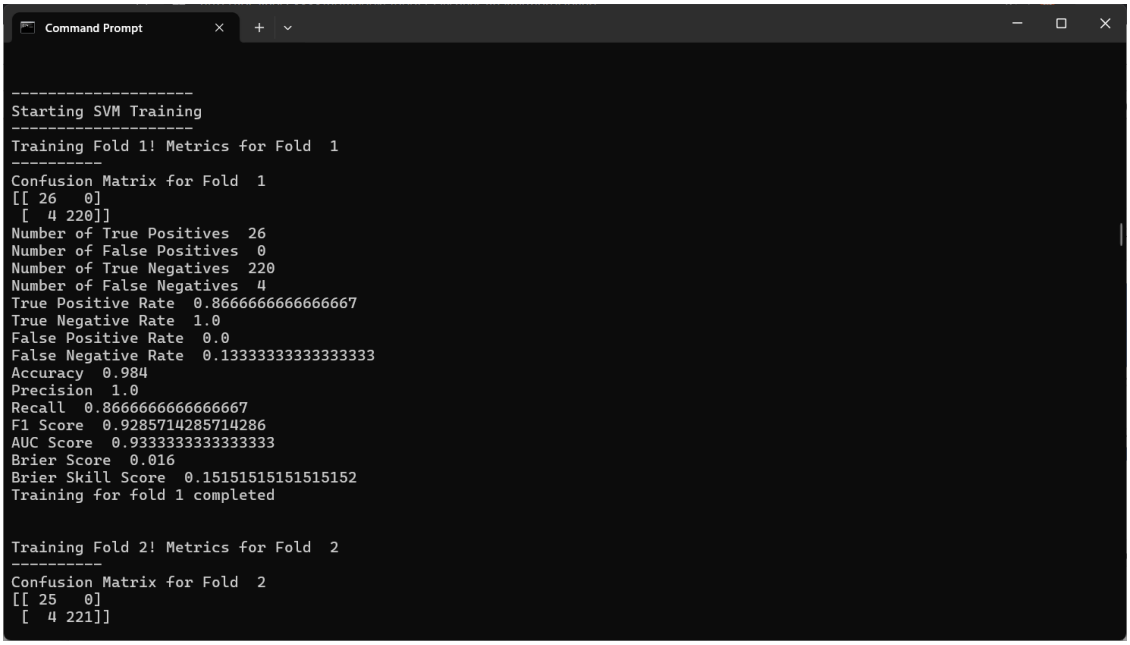
[147]:
```
Image("ss/29.png")
```

[147]:



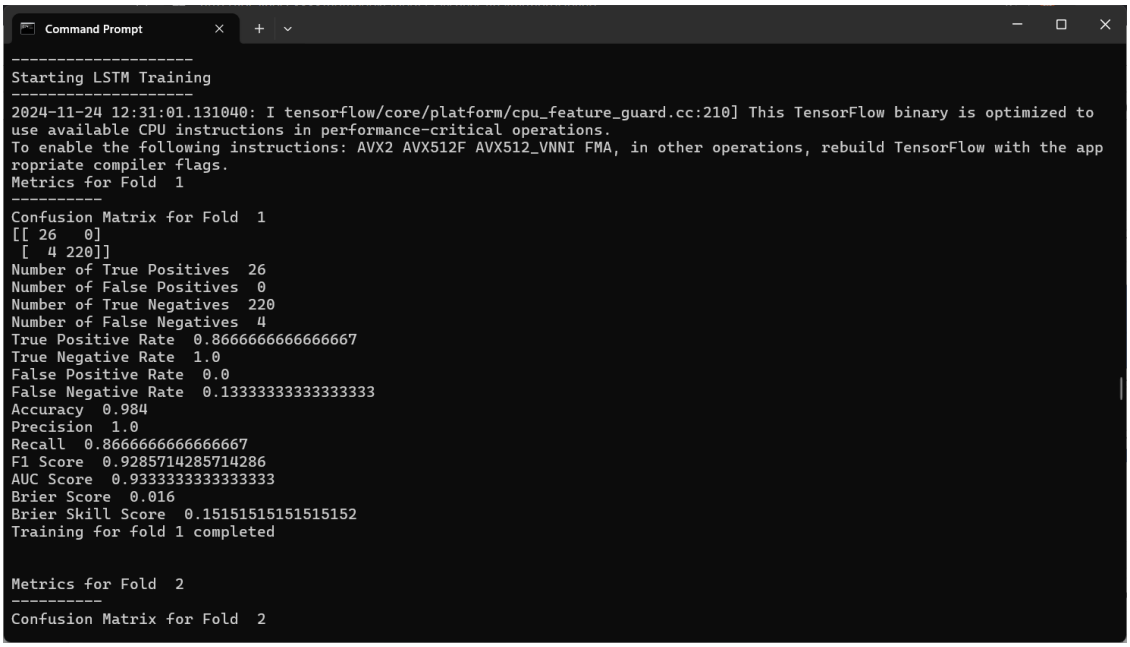
[148]:
```
Image("ss/30.png")
```

[148]:



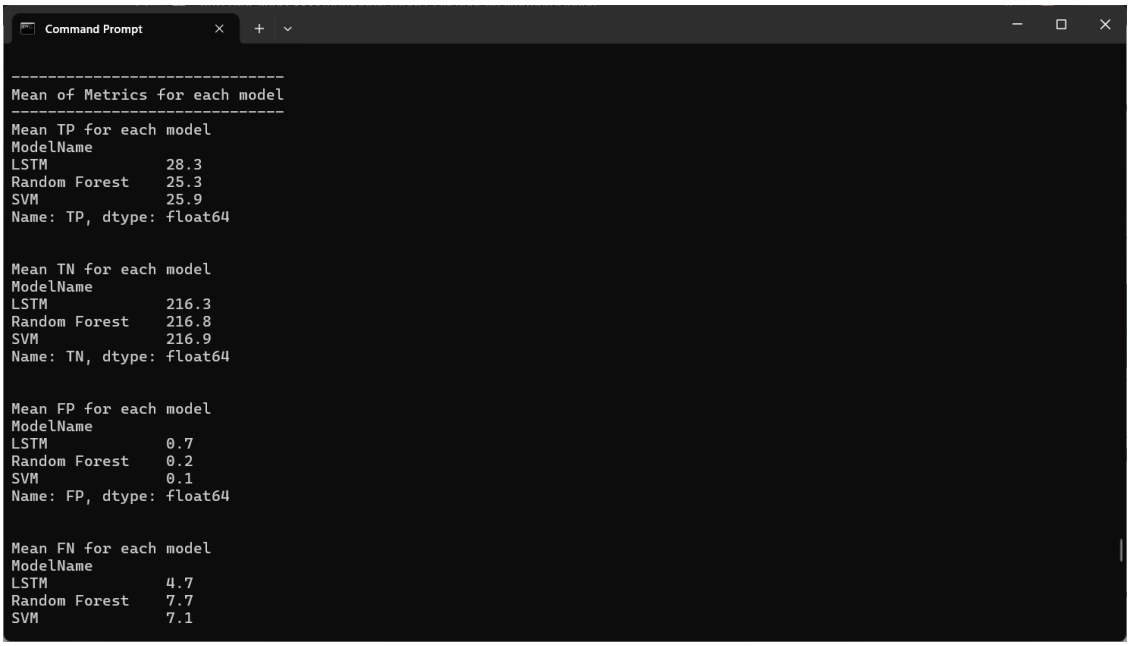
[149]:
```
Image("ss/31.png")
```

[149]:



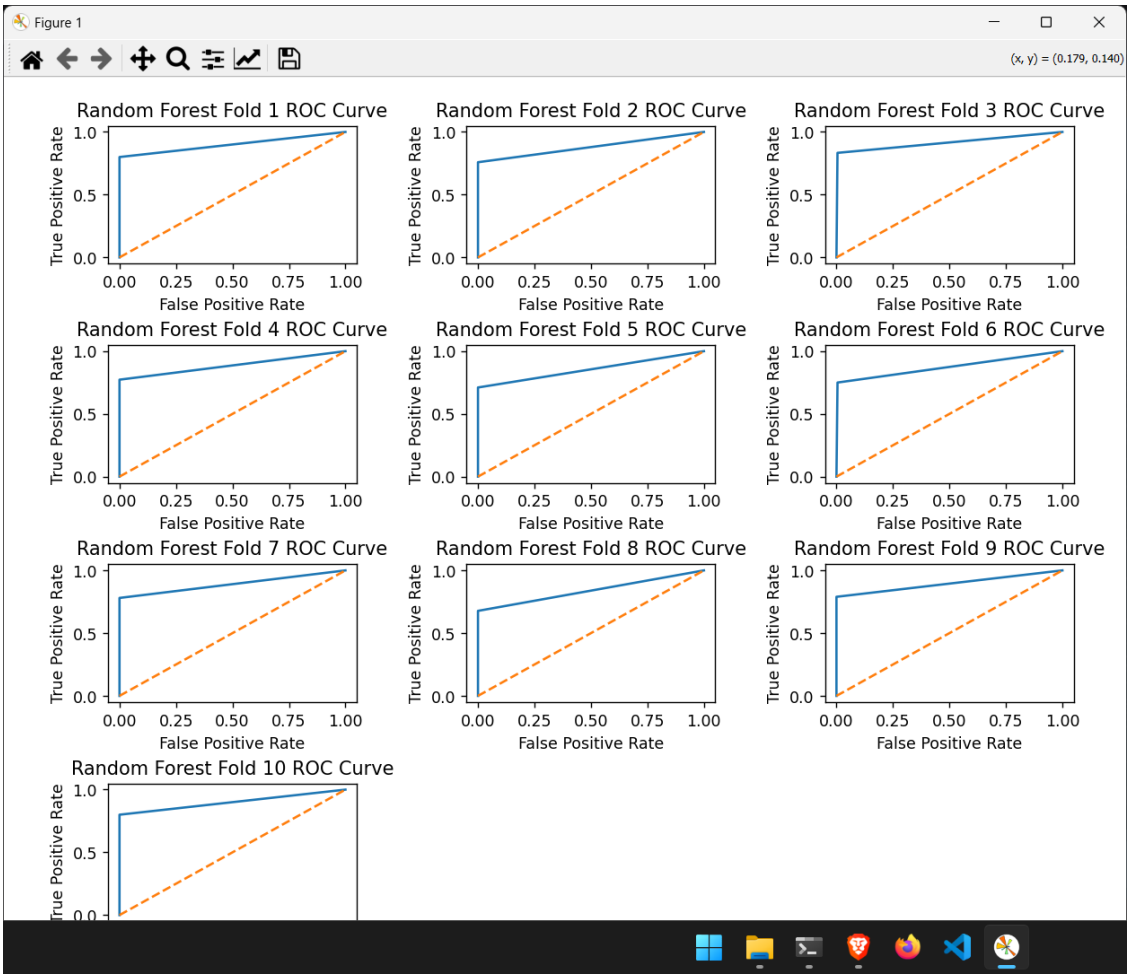
[150]:
```
Image("ss/32.png")
```

[150]:



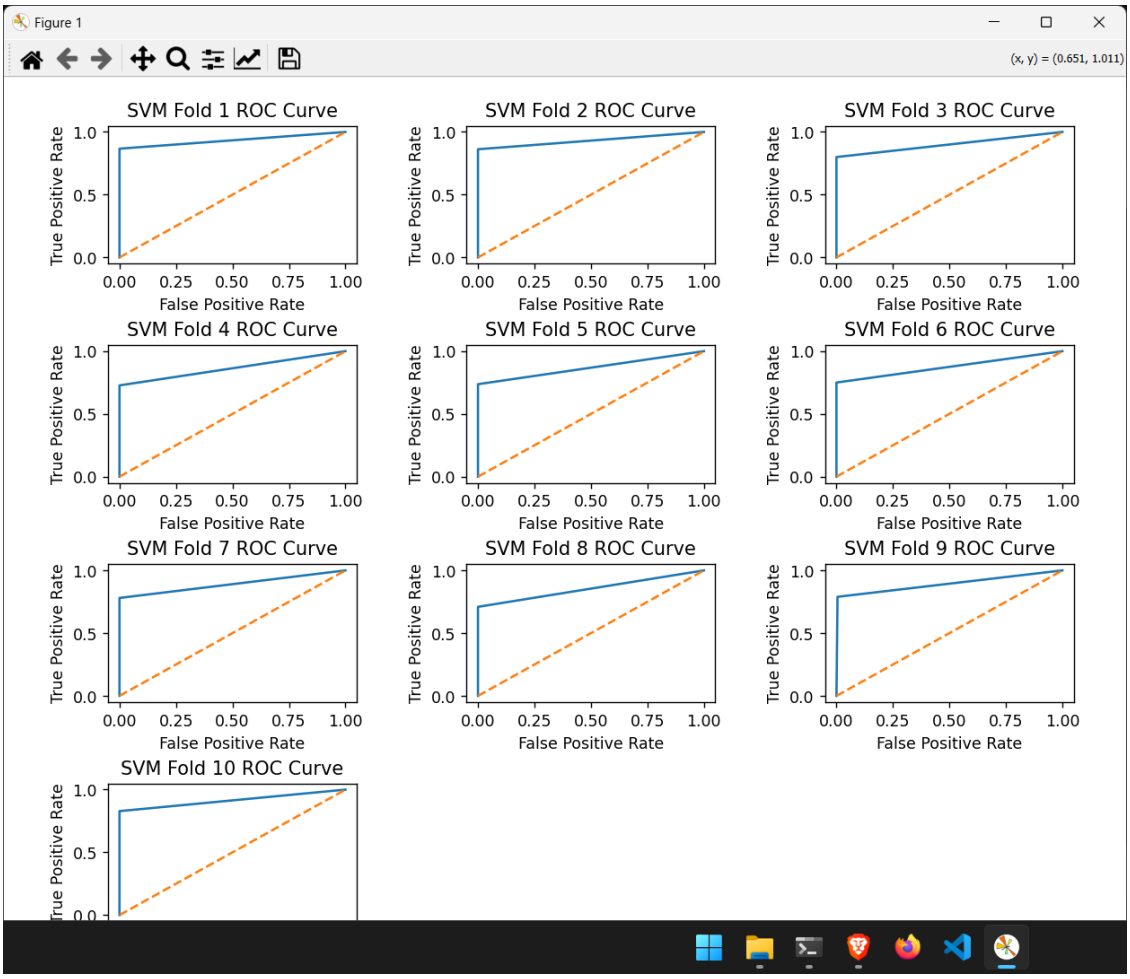
[151]:
```
Image("ss/33.png")
```

[151]:



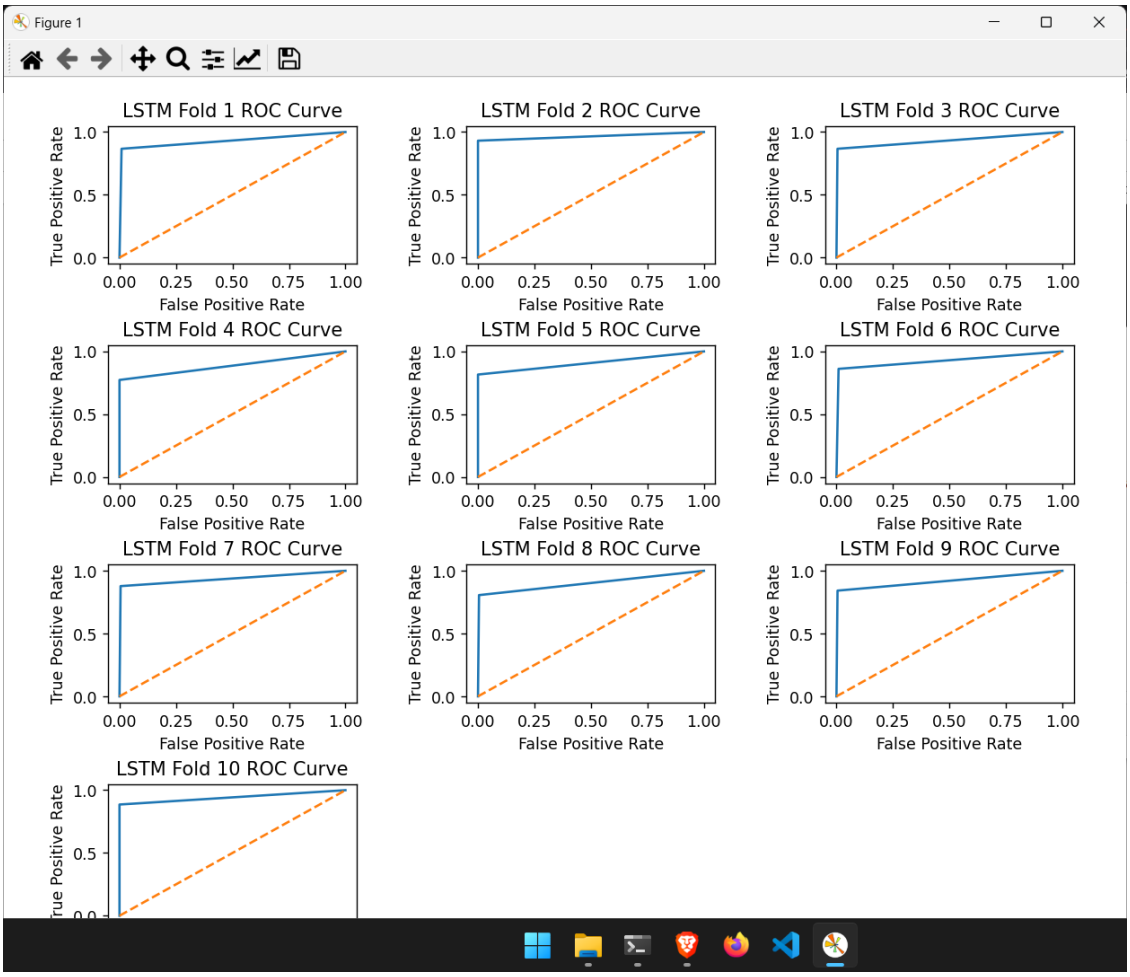
[152]:
```
Image("ss/34.png")
```

[152]:



[153]:
```
Image("ss/35.png")
```

[153]:



13 Output

- When executing the code in terminal we see all the metrics that are calculated for each fold when training each model on 10 Fold.
- We successfully train the model on all the folds and generating graphs for ROC Curve
- We also print the comparison of mean of metrics for all the models in our terminal. Which shows mean of a metric across all 3 models

14 Other

The source code (.py file) and data sets (.csv files) will be attached to the zip file.

Link to GitHub repository https://github.com/jaysheeldodianjit/dodia_jaysheel_finalproject