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Course: CS 634 101 Data Mining

GitHub: https://github.com/andrew-dragoslavic/Dragoslavic_Andrew_FinalTermProj

Import Packages

In [1]:
```
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, brier_score_loss, roc_curve, roc_auc_
from sklearn.model_selection import KFold
import matplotlib.pyplot as plt
from sklearn import svm
from keras.src.models import Sequential
from keras.src.layers import LSTM, Dense, Dropout, Input
from sklearn.preprocessing import StandardScaler
from keras.src.optimizers import Adam
```

```
/Users/andrewdragoslavic/Library/Python/3.9/lib/python/site-packages/urllib3/__init__.py:35: NotOpenSSLWarn
ing: urllib3 v2 only supports OpenSSL 1.1.1+, currently the 'ssl' module is compiled with 'LibreSSL 2.8.3'.
See: https://github.com/urllib3/urllib3/issues/3020
  warnings.warn(
```

Metrics and Their Formulas

True Positive Rate (TPR)

$$TPR = \frac{TP}{TP + FN}$$

True Negative Rate (TNR)

$$TNR = \frac{TN}{TN + FP}$$

False Positive Rate (FPR)

$$FPR = \frac{FP}{FP + TN}$$

False Negative Rate (FNR)

$$FNR = \frac{FN}{TP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

F1 Score

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} =$$

$$F1 = 2 \cdot \frac{TP}{2 \cdot TP + FP + FN}$$

Error Rate

$$Error\ Rate = \frac{FP + FN}{TP + TN + FP + FN}$$

Balanced Accuracy (BACC)

$$BACC = \frac{TPR + TNR}{2} = \frac{1}{2}\left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right)$$

True Skill Statistics (TSS)

TSS measures the difference between recall and the probability of false detection.

$$TSS = \frac{TP}{TP + FN} - \frac{FP}{FP + TN}$$

Heidke Skill Score (HSS)

HSS measures the fractional prediction over random prediction.

$$HSS = \frac{2(TP \cdot TN - FP \cdot FN)}{(TP + FN) \cdot (FN + TN) + (TP + FP) \cdot (FP + TN)}$$

Brier Score

$$\text{Brier Score} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Brier Skill Score (BSS)

$$BSS = \frac{\text{BS}}{\frac{1}{m}\sum_{n=1}^{m}(y_n - \bar{y})^2}$$

In [2]:
```
def calculate_metrics(FP, FN, TP, TN):
    P = TP + FN
    N = TN + FP
```

```
    TPR = TP/P if P != 0 else 0
    TNR = TN/N if N != 0 else 0
    FPR = FP/N if N != 0 else 0
    FNR = FN/P if P != 0 else 0

    recall = TPR
    precision = TP/(TP+FP) if (TP+FP) != 0 else 0
    F1 = (2*TP)/(2*TP+FP+FN) if (2*TP+FP+FN) != 0 else 0
    accuracy = (TP+TN)/(TP+TN+FP+FN) if (TP+TN+FP+FN) != 0 else 0
    error_rate = (FP+FN)/(TP+TN+FP+FN) if (TP+TN+FP+FN) != 0 else 0

    BACC = (TPR+TNR)/2
    TSS = ((TP / (TP + FN)) - (FP / (FP + TN))) if (TP + FN > 0 and FP + TN > 0) else 0
    HSS = (2*((TP*TN)-(FP*FN)))/(((TP+FN)*(FN+TN)) + ((TP+FP)*(FP+TN))) if ((((TP+FN)*(FN+TN)) + ((TP+FP)*

    return {
        'TP': TP,
        'TN': TN,
        'FP': FP,
        'FN': FN,
        'TPR': TPR,
        'TNR': TNR,
        'FPR': FPR,
        'FNR': FNR,
        'Recall': recall,
        'Precision': precision,
        'F1': F1,
        'Accuracy': accuracy,
        'Error Rate': error_rate,
        'BACC': BACC,
        'TSS': TSS,
        'HSS': HSS
    }
```

Function: `random_forest`

- **Purpose**: Trains a Random Forest classifier and evaluates its performance
- **Inputs**:
  - `X_train`, `X_test`: Training and test feature sets

- `y_train`, `y_test`: Training and test labels
- **Steps**:
  - Initializes a `RandomForestClassifier`
  - Fits the classifier to the training data
  - Predicts the class labels (`y_pred`) for the test data
  - Predicts class probabilities (`y_prob`) for the test data
  - Calculates the **Brier score** to measure the accuracy of probabilistic predictions
  - Computes the **ROC AUC** to evaluate classifier performance
- **Outputs**:
  - A dictionary containing:
    - `y_pred`: Predicted class labels
    - `y_prob`: Predicted probabilities
    - `brier_score`: Brier score for the predicted probabilities
    - `roc_auc`: ROC AUC score

In [3]:
```
def random_forest(X_train, X_test, y_train, y_test):
    rf  = RandomForestClassifier()
    rf.fit(X_train, y_train)

    y_pred = rf.predict(X_test)
    y_prob = rf.predict_proba(X_test)[:, 1]
    brier_score = brier_score_loss(y_test,y_prob)
    roc_auc = roc_auc_score(y_test, y_prob)

    return {
        'y_pred': y_pred,
        'y_prob': y_prob,
        'brier_score': brier_score,
        'roc_auc': roc_auc
    }
```

Function: `support_vector_machine`

- **Purpose**: Trains a Support Vector Classifier and evaluates its performance.
- **Inputs**:

    - `X_train`, `X_test`: Training and test feature sets.
    - `y_train`, `y_test`: Training and test labels.
- **Steps**:
    - Initializes a `SVC` with `kernel=linear`
    - Fits the classifier to the training data
    - Predicts the class labels (`y_pred`) for the test data
    - Predicts class probabilities (`y_prob`) for the test data
    - Calculates the **Brier score** to measure the accuracy of probabilistic predictions
    - Computes the **ROC AUC** to evaluate classifier performance
- **Outputs**:
    - A dictionary containing:
        - `y_pred`: Predicted class labels
        - `y_prob`: Predicted probabilities
        - `brier_score`: Brier score for the predicted probabilities
        - `roc_auc`: ROC AUC score

In [4]:
```
def support_vector_machine(X_train, X_test, y_train, y_test):
    clf = svm.SVC(kernel='linear', probability=True)
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    y_prob = clf.predict_proba(X_test)[:, 1]
    brier_score = brier_score_loss(y_test,y_prob)
    roc_auc = roc_auc_score(y_test, y_prob)

    return {
        'y_pred': y_pred,
        'y_prob': y_prob,
        'brier_score': brier_score,
        'roc_auc': roc_auc
    }
```

Function: `lstm`

This function trains an LSTM model for binary classification. The steps are:

- **Standardize the Input:**

    - Applies `StandardScaler` to normalize `X_train` and `X_test`.
- **Reshape Data:**
    - Reshapes the data to 3D format (`[samples, time steps, features]`) for LSTM input.
- **Define the LSTM Model:**
    - Creates an LSTM model with:
        - An input layer for time series data.
        - An LSTM layer with 50 units and ReLU activation.
        - Dropout regularization to prevent overfitting.
        - A Dense output layer with a sigmoid activation for binary classification.
- **Compile the Model:**
    - Optimized using the Adam optimizer and binary cross-entropy loss.
- **Train the Model:**
    - Trains the model using the provided training data for 50 epochs and a batch size of 32.
- **Generate Predictions:**
    - Predicts probabilities (`y_prob`) for the test data.
    - Converts probabilities to binary class predictions (`y_pred`) using a threshold of 0.5.
- **Calculate Metrics:**
    - Computes:
        - **Brier Score:** Measures the accuracy of predicted probabilities.
        - **ROC AUC:** Evaluates the model's ability to distinguish between classes.
- **Return Values:**
    - Returns a dictionary containing:
        - `y_pred` : Predicted binary classes.
        - `y_prob` : Predicted probabilities.
        - `brier_score` : Brier score for predictions.
        - `roc_auc` : ROC AUC score for the model.

In [5]:
```
def lstm(X_train, X_test, y_train, y_test):
    scaler = StandardScaler()
    X_train = scaler.fit_transform(X_train)
    X_test = scaler.transform(X_test)

    X_train = X_train.reshape((X_train.shape[0], 1, X_train.shape[1]))
    X_test = X_test.reshape((X_test.shape[0], 1, X_test.shape[1]))

    # Define the LSTM model with Input layer
    lstm_model = Sequential([
        Input(shape=(X_train.shape[1], X_train.shape[2])),
        LSTM(50, activation='relu'),
        Dropout(0.2),
        Dense(1, activation='sigmoid')
    ])
    lstm_model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])

    # Train the LSTM model
    lstm_model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=0)

    # Predict and convert probabilities to binary labels
    y_pred_prob = lstm_model.predict(X_test)
    brier_score = brier_score_loss(y_test, y_pred_prob)
    roc_auc = roc_auc_score(y_test, y_pred_prob)
    y_pred = (y_pred_prob > 0.5).astype(int).flatten()

    return {
        'y_pred': y_pred,
        'y_prob': y_pred_prob,
        'brier_score': brier_score,
        'roc_auc': roc_auc
    }
```

Function: `plot_roc`

This function plots the ROC Curve for each model and diplay the AUC value. The steps are

- **`plt.figure()`** : Initialize the figure
- **`plt.plot(fpr, tpr, color='blue', label=f'ROC curve (AUC = {roc_auc:.2f})')`**

  - Plots the ROC curve using the `fpr` (False Positive Rate) on the x-axis and the `tpr` (True Positive Rate) on the y-axis
  - Label with the `roc_auc` (Area Under Curve) value rounded to 2 decimal places
- **`plt.plot([0, 1], [0, 1], color='gray', linestyle='--')`**
  - Plots a diagnoal dashed line starting at the origin (0,0) and goes to (1,1)

In [6]:
```
def plot_roc(fpr, tpr, roc_auc, model_name):
    plt.figure()
    plt.plot(fpr, tpr, color='blue', label=f'ROC curve (AUC = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic (ROC) Curve - {model_name}')
    plt.legend(loc="lower right")
    plt.show()
```

Function: `eval_model`

- **`model_function(X_train, X_test, y_train, y_test)`**
  - Calls the specified model function either Random Forest, SVM, or LSTM
- **`y_pred`, `y_prob`, `brier_score`, and `roc_auc`**
  - Get the results from the model function that was called and store them in the respective variables
- **`all_y_true.extend(y_test)` and `all_y_prob.extend(y_prob)`**
  - Take the test values from each fold and store them in an array as well as the predicted probabilites and store them in an array
- **`cm = confusion_matrix(y_test, y_pred, labels=[1,0])`**
  - Create and confusion matrix using the test and predicted values and store the values from the confusion matrix in `FP`, `FN`, `TP`, `TN`
  - Add the confusion matrix from each fold to `cumulative_cm`
- **`fold_metrics = calculate_metrics(FP,FN,TP,TN)`**
  - Use the `calculate_metrics` function to get all the metrics and store them in `fold_metrics`
  - Add `brier_score`, `roc_auc`, and the current fold the the dictionary of all the metrics
- **`metrics_dict` and `metrics_list`**
  - Store all the values from the `fold_metrics` into the dictionary at `model_name` except the fold number

- Append the fold metrics to the list to display the information for all folds

In [7]:
```
def eval_model(model_name, model_function, X_train, X_test, y_train, y_test, all_y_true, all_y_prob, cumula
    res = model_function(X_train, X_test, y_train, y_test)
    y_pred = res['y_pred']
    y_prob = res['y_prob']
    brier_score = res['brier_score']
    roc_auc = res['roc_auc']
    all_y_true.extend(y_test)
    all_y_prob.extend(y_prob)

    reference_brier_score = brier_score_loss(y_test, reference_probs)
    brier_skill_score = 1 - (brier_score / reference_brier_score) if reference_brier_score != 0 else None

    cm = confusion_matrix(y_test, y_pred, labels=[1,0])
    TP, FN, FP, TN = cm[0,0], cm[0,1], cm[1,0], cm[1,1]
    cumulative_cm += cm
    fold_metrics = calculate_metrics(FP,FN,TP,TN)
    fold_metrics['Brier Score'] = brier_score
    fold_metrics['Brier Skill Score'] = brier_skill_score
    fold_metrics['AUC'] = roc_auc
    fold_metrics['Fold'] = i
    metrics_dict[model_name] = {key: value for key, value in fold_metrics.items() if key != 'Fold'}
    metrics_list.append(fold_metrics)

    return fold_metrics
```

Function: `process_metrics_dataframe`

This function processes a list of metrics dictionaries from cross-validation results, calculates the average of all numeric metrics, and appends these averages as a new row labeled "Average." The function returns a DataFrame with the fold-specific metrics and their averages

- **Input**:
    - A list of dictionaries (`metrics_list`), where each dictionary contains the metrics for a specific fold
- **Process**:
    1. **Convert to DataFrame**:

- The input list of dictionaries is converted into a pandas DataFrame, where each row represents a fold, and each column represents a metric
2. **Set `Fold` Column Type**:
   - The `Fold` column is converted to an object type to handle numeric folds and the Average label
3. **Calculate Averages**:
   - The mean is computed for all numeric columns in the DataFrame, ignoring non-numeric data and these averages are stored in a new row
4. **Add the Average Row**:
   - The calculated averages are appended as a new row labeled Average
5. **Set `Fold` as the Index**:
   - The `Fold` column is set as the DataFrame's index for better organization and readability

In [8]:
```
def process_metrics_dataframe(metrics_list):
    df = pd.DataFrame(metrics_list)
    df["Fold"] = df["Fold"].astype(object)
    averages = df.mean(numeric_only=True)
    averages["Fold"] = "Average"
    df = pd.concat([df, pd.DataFrame([averages])], ignore_index=True)
    df.set_index("Fold", inplace=True)
    return df
```

Function: `k_fold`

- **`KFold(n_splits=K, shuffle = True, random_state=42)`**
  - Use built in function to divide the dataset into K number of splits
- **Initialize lists, dictionaries, and confusion matrices for each model**
  - Make sure each model has a `metrics_list` to help make the data frame after all folds
  - Create a `cumulative_cm` for each model to display after all folds
  - Store prediction results and actual values in `all_y_true` and `all_y_prob`
- **Create the train and test data**
  - The `kf.split(X)` method to assign certain indices to the `train_index` and `test_index` for each fold
  - Use the `.iloc` method to index the values set from splitting the data to get the training data and the testing data
- **Getting Results from each Model**
  - Call the `eval_model` function passing in each models specific parameters in order to get the results for each fold

- **DataFrame Information**
  - Use `metrics_dict` which has the metrics for each model and convert it to a DataFrame
  - Print the data frame with the current fold to see the performance of each model after each fold
- **Getting DataFrame of Each Model**
  - Use the `process_metrics_dataframe` function to convert each models `metrics_list` into a DataFrame
  - Print the DataFrame for each model after all folds execute
- **Displaying ROC Curves and Confusion Matrices**
  - Go through `models` list and use the `y_true` and `y_prob` values in each tuple to find the `fpr`, `tpr` and the `roc_auc` values
  - Call the `plot_roc` function in order to plot the ROC curve for each model passing in the previously calculated values
  - Call the `ConfusionMatrixDisplay` function and pass in the `cumulative_cm` for each model to see the confusion matrix for each model

In [9]:
```
def k_fold(X, Y, K):
    kf = KFold(n_splits=K, shuffle = True, random_state=42)
    metrics_list_rf, metrics_list_clf, metrics_list_lstm = [], [], []
    metrics_dict = {}
    cumulative_cm_rf,cumulative_cm_clf, cumulative_cm_lstm = np.zeros((2, 2), dtype=int), np.zeros((2, 2),
    all_y_true_rf, all_y_true_clf, all_y_true_lstm  = [], [], []
    all_y_prob_rf, all_y_prob_clf, all_y_prob_lstm = [], [], []

    for i, (train_index, test_index) in enumerate(kf.split(X), start = 1):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = Y.iloc[train_index], Y.iloc[test_index]
        reference_prob = y_train.mean()
        reference_probs = pd.Series([reference_prob] * len(test_index), index=test_index)

        eval_model(
            model_name='Random Forest', model_function=random_forest,
            X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
            all_y_true=all_y_true_rf, all_y_prob=all_y_prob_rf, cumulative_cm=cumulative_cm_rf,
            metrics_dict=metrics_dict, metrics_list=metrics_list_rf, i = i, reference_probs=reference_probs
        )

        eval_model(
            model_name='SVM', model_function=support_vector_machine,
```

```
            X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
            all_y_true=all_y_true_clf, all_y_prob=all_y_prob_clf, cumulative_cm=cumulative_cm_clf,
            metrics_dict=metrics_dict, metrics_list=metrics_list_clf, i = i, reference_probs=reference_prol
        )

        eval_model(
            model_name='LSTM', model_function=lstm,
            X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
            all_y_true=all_y_true_lstm, all_y_prob=all_y_prob_lstm, cumulative_cm=cumulative_cm_lstm,
            metrics_dict=metrics_dict, metrics_list=metrics_list_lstm, i = i, reference_probs=reference_pr
        )

        df = pd.DataFrame(metrics_dict)
        print(f"\nFold {i}:\n{df}")

    df_rf = process_metrics_dataframe(metrics_list_rf)
    df_clf = process_metrics_dataframe(metrics_list_clf)
    df_lstm = process_metrics_dataframe(metrics_list_lstm)

    print(f"\nRandom Forest Metrics:\n{df_rf}")
    print(f"\nSVM Metrics:\n{df_clf}")
    print(f"\nLSTM Metrics:\n{df_lstm}")

    models = [
        ('Random Forest', all_y_true_rf, all_y_prob_rf, cumulative_cm_rf),
        ('SVM', all_y_true_clf, all_y_prob_clf, cumulative_cm_clf),
        ('LSTM', all_y_true_lstm, all_y_prob_lstm, cumulative_cm_lstm)
    ]

    for model_name, y_true, y_prob, cm in models:
        fpr, tpr, _ = roc_curve(y_true, y_prob)
        roc_auc = roc_auc_score(y_true, y_prob)
        plot_roc(fpr,tpr, roc_auc, model_name)

        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=[1,0])
        disp.plot(cmap='Blues')
        plt.title(f'Cumulative Confusion Matrix After All Folds - {model_name}')
        plt.show()
```

Execution

- **Read the Data**
  - Get the data from CSV file and store in `data` variable
- **Display Setting**
  - Make sure all rows and columns are displayed on execution
- **Splitting Data**
  - Set the `X` variable to all the values in the DataFrame excluding the `target` column
  - Set the `Y` variable to the values in the `target` column
- **Executing**
  - Call the `k_fold` function to run all the model on the data and set the number of folds to 10

In [10]:

```
data = pd.read_csv("Data/heart.csv")
pd.set_option('display.width', 100)
pd.set_option('display.max_rows', None)  # Show all rows
pd.set_option('display.max_columns', None)

X = data.drop('target', axis=1)
Y = data['target']

k_fold(X,Y,10)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step

Fold 1:
                   Random Forest        SVM       LSTM
TP                     13.000000  15.000000  15.000000
TN                     10.000000  11.000000  11.000000
FP                      4.000000   3.000000   3.000000
FN                      4.000000   2.000000   2.000000
TPR                     0.764706   0.882353   0.882353
TNR                     0.714286   0.785714   0.785714
FPR                     0.285714   0.214286   0.214286
FNR                     0.235294   0.117647   0.117647
Recall                  0.764706   0.882353   0.882353
Precision               0.764706   0.833333   0.833333
F1                      0.764706   0.857143   0.857143
Accuracy                0.741935   0.838710   0.838710
Error Rate              0.258065   0.161290   0.161290
BACC                    0.739496   0.834034   0.834034
TSS                     0.478992   0.668067   0.668067
HSS                     0.478992   0.672304   0.672304
Brier Score             0.152710   0.135433   0.154930
Brier Skill Score       0.383432   0.453188   0.374467
AUC                     0.855042   0.890756   0.869748
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step

Fold 2:
                   Random Forest        SVM       LSTM
TP                     15.000000  15.000000  15.000000
TN                     14.000000  14.000000  14.000000
FP                      1.000000   1.000000   1.000000
FN                      1.000000   1.000000   1.000000
TPR                     0.937500   0.937500   0.937500
TNR                     0.933333   0.933333   0.933333
FPR                     0.066667   0.066667   0.066667
FNR                     0.062500   0.062500   0.062500
Recall                  0.937500   0.937500   0.937500
Precision               0.937500   0.937500   0.937500
F1                      0.937500   0.937500   0.937500
Accuracy                0.935484   0.935484   0.935484
Error Rate              0.064516   0.064516   0.064516
BACC                    0.935417   0.935417   0.935417
TSS                     0.870833   0.870833   0.870833
```

```
HSS                      0.870833   0.870833   0.870833
Brier Score              0.072723   0.073110   0.072729
Brier Skill Score        0.709971   0.708426   0.709945
AUC                      0.977083   0.954167   0.937500
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step

Fold 3:
                   Random Forest        SVM       LSTM
TP                     15.000000  16.000000  17.000000
TN                      8.000000   7.000000   8.000000
FP                      4.000000   5.000000   4.000000
FN                      4.000000   3.000000   2.000000
TPR                     0.789474   0.842105   0.894737
TNR                     0.666667   0.583333   0.666667
FPR                     0.333333   0.416667   0.333333
FNR                     0.210526   0.157895   0.105263
Recall                  0.789474   0.842105   0.894737
Precision               0.789474   0.761905   0.809524
F1                      0.789474   0.800000   0.850000
Accuracy                0.741935   0.741935   0.806452
Error Rate              0.258065   0.258065   0.193548
BACC                    0.728070   0.712719   0.780702
TSS                     0.456140   0.425439   0.561404
HSS                     0.456140   0.438914   0.579186
Brier Score             0.156310   0.178071   0.147979
Brier Skill Score       0.356882   0.267348   0.391158
AUC                     0.837719   0.776316   0.837719
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step

Fold 4:
                   Random Forest        SVM       LSTM
TP                     14.000000  16.000000  16.000000
TN                     11.000000   9.000000  10.000000
FP                      1.000000   3.000000   2.000000
FN                      4.000000   2.000000   2.000000
TPR                     0.777778   0.888889   0.888889
TNR                     0.916667   0.750000   0.833333
FPR                     0.083333   0.250000   0.166667
FNR                     0.222222   0.111111   0.111111
Recall                  0.777778   0.888889   0.888889
Precision               0.933333   0.842105   0.888889
F1                      0.848485   0.864865   0.888889
```

```
Accuracy                0.833333   0.833333   0.866667
Error Rate              0.166667   0.166667   0.133333
BACC                    0.847222   0.819444   0.861111
TSS                     0.694444   0.638889   0.722222
HSS                     0.666667   0.647887   0.722222
Brier Score             0.113287   0.138700   0.120834
Brier Skill Score       0.535305   0.431059   0.504348
AUC                     0.912037   0.870370   0.907407
WARNING:tensorflow:5 out of the last 5 calls to <function TensorFlowTrainer.make_predict_function.<locals>.
one_step_on_data_distributed at 0x179ef8940> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing te
nsors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @t
f.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnec
essary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing
and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step

Fold 5:
                   Random Forest        SVM       LSTM
TP                     11.000000  12.000000  12.000000
TN                     15.000000  13.000000  15.000000
FP                      2.000000   4.000000   2.000000
FN                      2.000000   1.000000   1.000000
TPR                     0.846154   0.923077   0.923077
TNR                     0.882353   0.764706   0.882353
FPR                     0.117647   0.235294   0.117647
FNR                     0.153846   0.076923   0.076923
Recall                  0.846154   0.923077   0.923077
Precision               0.846154   0.750000   0.857143
F1                      0.846154   0.827586   0.888889
Accuracy                0.866667   0.833333   0.900000
Error Rate              0.133333   0.166667   0.100000
BACC                    0.864253   0.843891   0.902715
TSS                     0.728507   0.687783   0.805430
HSS                     0.728507   0.669604   0.798206
Brier Score             0.131793   0.118201   0.114991
Brier Skill Score       0.494645   0.546763   0.559074
AUC                     0.911765   0.923077   0.927602
WARNING:tensorflow:6 out of the last 6 calls to <function TensorFlowTrainer.make_predict_function.<locals>.
one_step_on_data_distributed at 0x17c5e8af0> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing te
nsors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @t
```

```
f.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnec
essary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing
and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step

Fold 6:
                   Random Forest        SVM       LSTM
TP                     17.000000  17.000000  16.000000
TN                      8.000000   9.000000   9.000000
FP                      4.000000   3.000000   3.000000
FN                      1.000000   1.000000   2.000000
TPR                     0.944444   0.944444   0.888889
TNR                     0.666667   0.750000   0.750000
FPR                     0.333333   0.250000   0.250000
FNR                     0.055556   0.055556   0.111111
Recall                  0.944444   0.944444   0.888889
Precision               0.809524   0.850000   0.842105
F1                      0.871795   0.894737   0.864865
Accuracy                0.833333   0.866667   0.833333
Error Rate              0.166667   0.133333   0.166667
BACC                    0.805556   0.847222   0.819444
TSS                     0.611111   0.694444   0.638889
HSS                     0.637681   0.714286   0.647887
Brier Score             0.112733   0.128065   0.135423
Brier Skill Score       0.537574   0.474686   0.444502
AUC                     0.942130   0.888889   0.893519
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step

Fold 7:
                   Random Forest        SVM       LSTM
TP                     13.000000  13.000000  13.000000
TN                      9.000000   9.000000   8.000000
FP                      6.000000   6.000000   7.000000
FN                      2.000000   2.000000   2.000000
TPR                     0.866667   0.866667   0.866667
TNR                     0.600000   0.600000   0.533333
FPR                     0.400000   0.400000   0.466667
FNR                     0.133333   0.133333   0.133333
Recall                  0.866667   0.866667   0.866667
Precision               0.684211   0.684211   0.650000
F1                      0.764706   0.764706   0.742857
Accuracy                0.733333   0.733333   0.700000
```

```
Error Rate              0.266667   0.266667   0.300000
BACC                    0.733333   0.733333   0.700000
TSS                     0.466667   0.466667   0.400000
HSS                     0.466667   0.466667   0.400000
Brier Score             0.180900   0.156862   0.177079
Brier Skill Score       0.283409   0.378630   0.298544
AUC                     0.817778   0.884444   0.848889
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 48ms/step

Fold 8:
                   Random Forest        SVM       LSTM
TP                     16.000000  18.000000  16.000000
TN                      9.000000   7.000000   7.000000
FP                      3.000000   5.000000   5.000000
FN                      2.000000   0.000000   2.000000
TPR                     0.888889   1.000000   0.888889
TNR                     0.750000   0.583333   0.583333
FPR                     0.250000   0.416667   0.416667
FNR                     0.111111   0.000000   0.111111
Recall                  0.888889   1.000000   0.888889
Precision               0.842105   0.782609   0.761905
F1                      0.864865   0.878049   0.820513
Accuracy                0.833333   0.833333   0.766667
Error Rate              0.166667   0.166667   0.233333
BACC                    0.819444   0.791667   0.736111
TSS                     0.638889   0.583333   0.472222
HSS                     0.647887   0.626866   0.492754
Brier Score             0.134673   0.118180   0.120277
Brier Skill Score       0.447578   0.515232   0.506629
AUC                     0.902778   0.935185   0.916667
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step

Fold 9:
                   Random Forest        SVM       LSTM
TP                     12.000000  13.000000  13.000000
TN                     14.000000  13.000000  13.000000
FP                      1.000000   2.000000   2.000000
FN                      3.000000   2.000000   2.000000
TPR                     0.800000   0.866667   0.866667
TNR                     0.933333   0.866667   0.866667
FPR                     0.066667   0.133333   0.133333
FNR                     0.200000   0.133333   0.133333
```

```
Recall                0.800000   0.866667   0.866667
Precision             0.923077   0.866667   0.866667
F1                    0.857143   0.866667   0.866667
Accuracy              0.866667   0.866667   0.866667
Error Rate            0.133333   0.133333   0.133333
BACC                  0.866667   0.866667   0.866667
TSS                   0.733333   0.733333   0.733333
HSS                   0.733333   0.733333   0.733333
Brier Score           0.099963   0.109738   0.109799
Brier Skill Score     0.604020   0.565300   0.565057
AUC                   0.940000   0.928889   0.924444
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step

Fold 10:
                   Random Forest        SVM       LSTM
TP                     14.000000  15.000000  15.000000
TN                     10.000000  11.000000  11.000000
FP                      4.000000   3.000000   3.000000
FN                      2.000000   1.000000   1.000000
TPR                     0.875000   0.937500   0.937500
TNR                     0.714286   0.785714   0.785714
FPR                     0.285714   0.214286   0.214286
FNR                     0.125000   0.062500   0.062500
Recall                  0.875000   0.937500   0.937500
Precision               0.777778   0.833333   0.833333
F1                      0.823529   0.882353   0.882353
Accuracy                0.800000   0.866667   0.866667
Error Rate              0.200000   0.133333   0.133333
BACC                    0.794643   0.861607   0.861607
TSS                     0.589286   0.723214   0.723214
HSS                     0.594595   0.729730   0.729730
Brier Score             0.112000   0.086829   0.103064
Brier Skill Score       0.550280   0.651351   0.586163
AUC                     0.937500   0.946429   0.924107

Random Forest Metrics:
           TP    TN   FP   FN       TPR       TNR       FPR       FNR    Recall  Precision  \
Fold
1        13.0  10.0  4.0  4.0  0.764706  0.714286  0.285714  0.235294  0.764706   0.764706
2        15.0  14.0  1.0  1.0  0.937500  0.933333  0.066667  0.062500  0.937500   0.937500
3        15.0   8.0  4.0  4.0  0.789474  0.666667  0.333333  0.210526  0.789474   0.789474
4        14.0  11.0  1.0  4.0  0.777778  0.916667  0.083333  0.222222  0.777778   0.933333
```

5	11.0	15.0	2.0	2.0	0.846154	0.882353	0.117647	0.153846	0.846154	0.846154
6	17.0	8.0	4.0	1.0	0.944444	0.666667	0.333333	0.055556	0.944444	0.809524
7	13.0	9.0	6.0	2.0	0.866667	0.600000	0.400000	0.133333	0.866667	0.684211
8	16.0	9.0	3.0	2.0	0.888889	0.750000	0.250000	0.111111	0.888889	0.842105
9	12.0	14.0	1.0	3.0	0.800000	0.933333	0.066667	0.200000	0.800000	0.923077
10	14.0	10.0	4.0	2.0	0.875000	0.714286	0.285714	0.125000	0.875000	0.777778
Average	14.0	10.8	3.0	2.5	0.849061	0.777759	0.222241	0.150939	0.849061	0.830786

Fold	F1	Accuracy	Error Rate	BACC	TSS	HSS	Brier Score \
1	0.764706	0.741935	0.258065	0.739496	0.478992	0.478992	0.152710
2	0.937500	0.935484	0.064516	0.935417	0.870833	0.870833	0.072723
3	0.789474	0.741935	0.258065	0.728070	0.456140	0.456140	0.156310
4	0.848485	0.833333	0.166667	0.847222	0.694444	0.666667	0.113287
5	0.846154	0.866667	0.133333	0.864253	0.728507	0.728507	0.131793
6	0.871795	0.833333	0.166667	0.805556	0.611111	0.637681	0.112733
7	0.764706	0.733333	0.266667	0.733333	0.466667	0.466667	0.180900
8	0.864865	0.833333	0.166667	0.819444	0.638889	0.647887	0.134673
9	0.857143	0.866667	0.133333	0.866667	0.733333	0.733333	0.099963
10	0.823529	0.800000	0.200000	0.794643	0.589286	0.594595	0.112000
Average	0.836836	0.818602	0.181398	0.813410	0.626820	0.628130	0.126709

Fold	Brier Skill Score	AUC
1	0.383432	0.855042
2	0.709971	0.977083
3	0.356882	0.837719
4	0.535305	0.912037
5	0.494645	0.911765
6	0.537574	0.942130
7	0.283409	0.817778
8	0.447578	0.902778
9	0.604020	0.940000
10	0.550280	0.937500
Average	0.490310	0.903383

SVM Metrics:

Fold	TP	TN	FP	FN	TPR	TNR	FPR	FNR	Recall	Precision \
1	15.0	11.0	3.0	2.0	0.882353	0.785714	0.214286	0.117647	0.882353	0.833333
2	15.0	14.0	1.0	1.0	0.937500	0.933333	0.066667	0.062500	0.937500	0.937500
3	16.0	7.0	5.0	3.0	0.842105	0.583333	0.416667	0.157895	0.842105	0.761905

4	16.0	9.0	3.0	2.0	0.888889	0.750000	0.250000	0.111111	0.888889	0.842105
5	12.0	13.0	4.0	1.0	0.923077	0.764706	0.235294	0.076923	0.923077	0.750000
6	17.0	9.0	3.0	1.0	0.944444	0.750000	0.250000	0.055556	0.944444	0.850000
7	13.0	9.0	6.0	2.0	0.866667	0.600000	0.400000	0.133333	0.866667	0.684211
8	18.0	7.0	5.0	0.0	1.000000	0.583333	0.416667	0.000000	1.000000	0.782609
9	13.0	13.0	2.0	2.0	0.866667	0.866667	0.133333	0.133333	0.866667	0.866667
10	15.0	11.0	3.0	1.0	0.937500	0.785714	0.214286	0.062500	0.937500	0.833333
Average	15.0	10.3	3.5	1.5	0.908920	0.740280	0.259720	0.091080	0.908920	0.814166

Fold	F1	Accuracy	Error Rate	BACC	TSS	HSS	Brier Score \
1	0.857143	0.838710	0.161290	0.834034	0.668067	0.672304	0.135433
2	0.937500	0.935484	0.064516	0.935417	0.870833	0.870833	0.073110
3	0.800000	0.741935	0.258065	0.712719	0.425439	0.438914	0.178071
4	0.864865	0.833333	0.166667	0.819444	0.638889	0.647887	0.138700
5	0.827586	0.833333	0.166667	0.843891	0.687783	0.669604	0.118201
6	0.894737	0.866667	0.133333	0.847222	0.694444	0.714286	0.128065
7	0.764706	0.733333	0.266667	0.733333	0.466667	0.466667	0.156862
8	0.878049	0.833333	0.166667	0.791667	0.583333	0.626866	0.118180
9	0.866667	0.866667	0.133333	0.866667	0.733333	0.733333	0.109738
10	0.882353	0.866667	0.133333	0.861607	0.723214	0.729730	0.086829
Average	0.857361	0.834946	0.165054	0.824600	0.649200	0.657042	0.124319

Fold	Brier Skill Score	AUC
1	0.453188	0.890756
2	0.708426	0.954167
3	0.267348	0.776316
4	0.431059	0.870370
5	0.546763	0.923077
6	0.474686	0.888889
7	0.378630	0.884444
8	0.515232	0.935185
9	0.565300	0.928889
10	0.651351	0.946429
Average	0.499198	0.899852

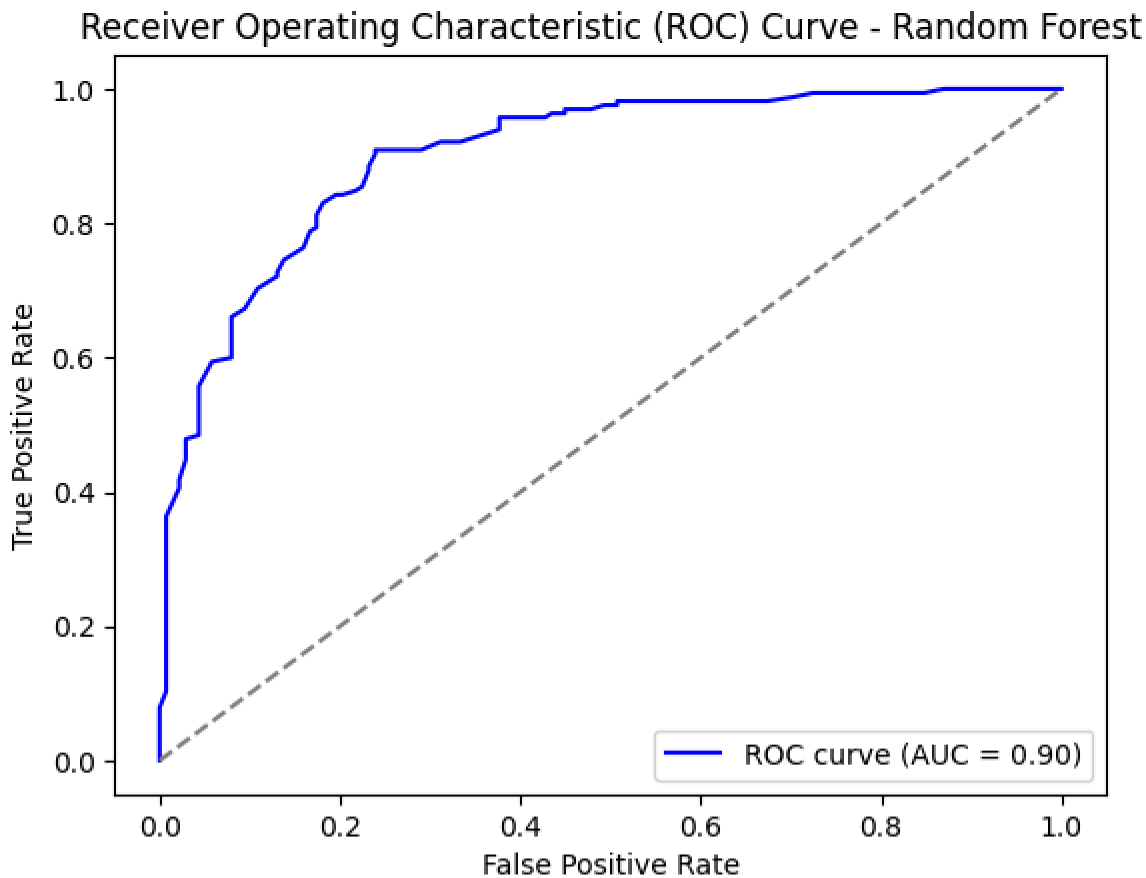
LSTM Metrics:

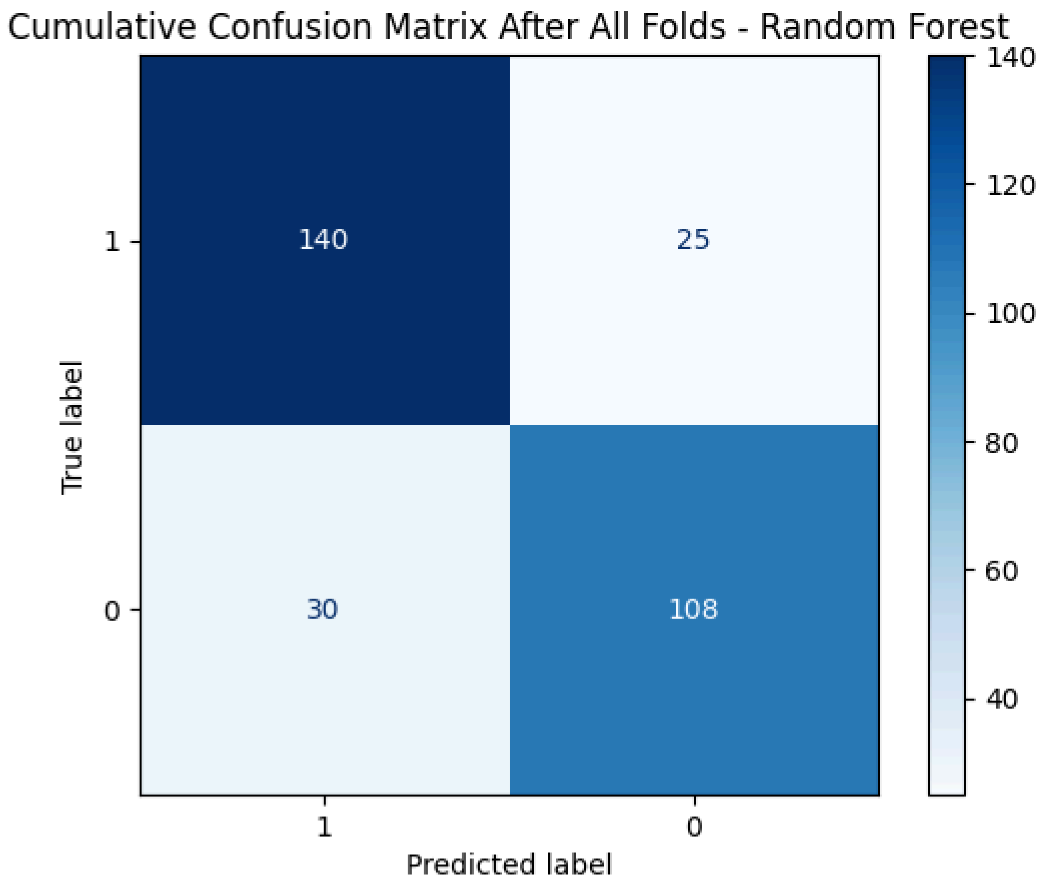
Fold	TP	TN	FP	FN	TPR	TNR	FPR	FNR	Recall	Precision \
1	15.0	11.0	3.0	2.0	0.882353	0.785714	0.214286	0.117647	0.882353	0.833333
2	15.0	14.0	1.0	1.0	0.937500	0.933333	0.066667	0.062500	0.937500	0.937500

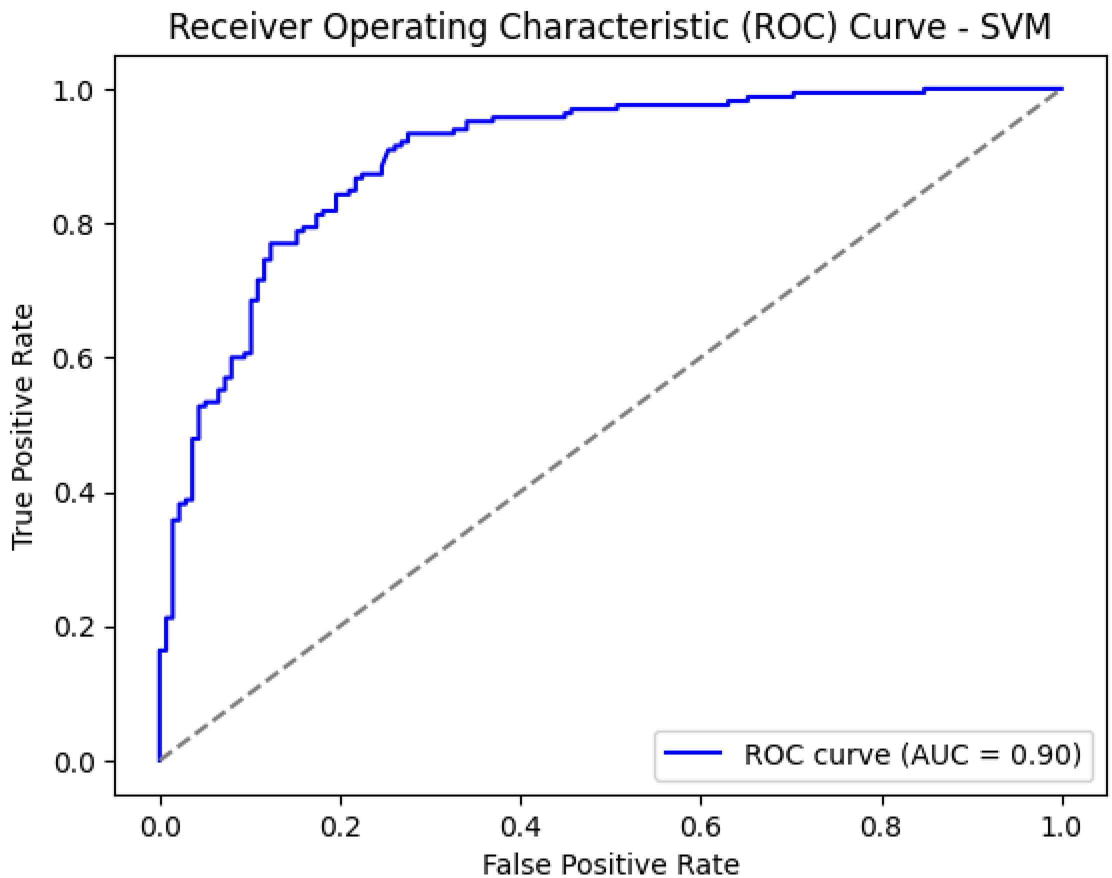
3	17.0	8.0	4.0	2.0	0.894737	0.666667	0.333333	0.105263	0.894737	0.809524
4	16.0	10.0	2.0	2.0	0.888889	0.833333	0.166667	0.111111	0.888889	0.888889
5	12.0	15.0	2.0	1.0	0.923077	0.882353	0.117647	0.076923	0.923077	0.857143
6	16.0	9.0	3.0	2.0	0.888889	0.750000	0.250000	0.111111	0.888889	0.842105
7	13.0	8.0	7.0	2.0	0.866667	0.533333	0.466667	0.133333	0.866667	0.650000
8	16.0	7.0	5.0	2.0	0.888889	0.583333	0.416667	0.111111	0.888889	0.761905
9	13.0	13.0	2.0	2.0	0.866667	0.866667	0.133333	0.133333	0.866667	0.866667
10	15.0	11.0	3.0	1.0	0.937500	0.785714	0.214286	0.062500	0.937500	0.833333
Average	14.8	10.6	3.2	1.7	0.897517	0.762045	0.237955	0.102483	0.897517	0.828040

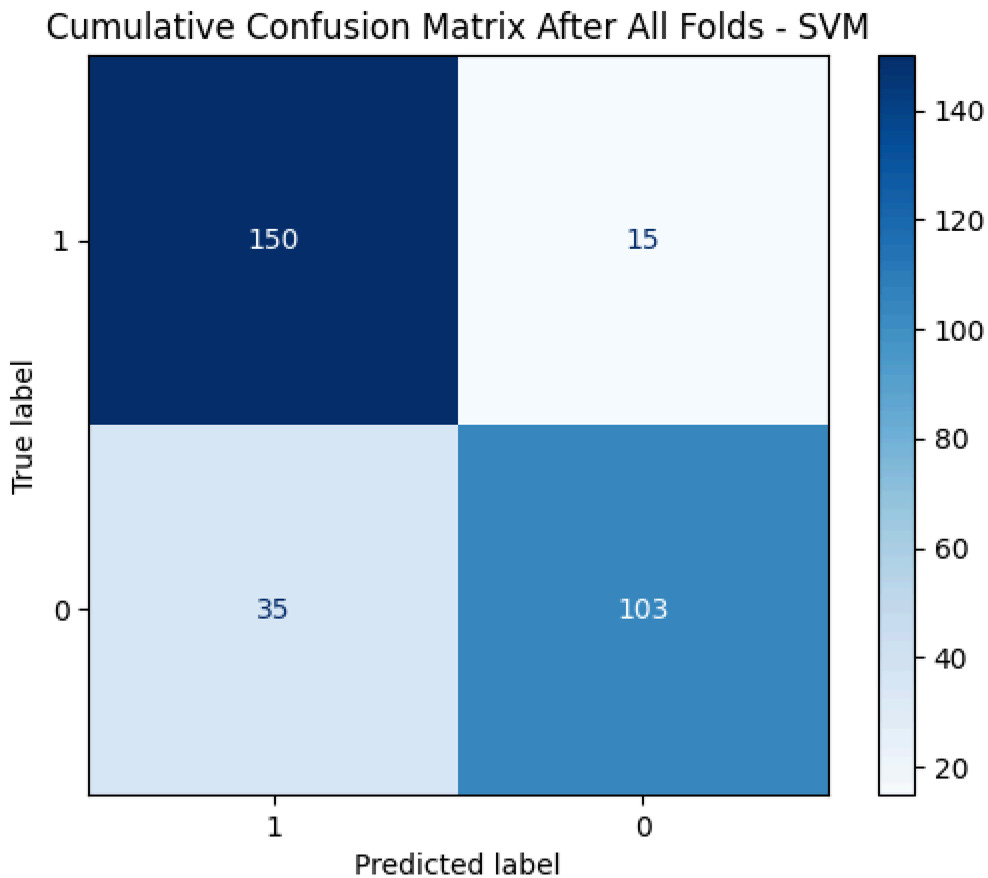
	F1	Accuracy	Error Rate	BACC	TSS	HSS	Brier Score \
Fold							
1	0.857143	0.838710	0.161290	0.834034	0.668067	0.672304	0.154930
2	0.937500	0.935484	0.064516	0.935417	0.870833	0.870833	0.072729
3	0.850000	0.806452	0.193548	0.780702	0.561404	0.579186	0.147979
4	0.888889	0.866667	0.133333	0.861111	0.722222	0.722222	0.120834
5	0.888889	0.900000	0.100000	0.902715	0.805430	0.798206	0.114991
6	0.864865	0.833333	0.166667	0.819444	0.638889	0.647887	0.135423
7	0.742857	0.700000	0.300000	0.700000	0.400000	0.400000	0.177079
8	0.820513	0.766667	0.233333	0.736111	0.472222	0.492754	0.120277
9	0.866667	0.866667	0.133333	0.866667	0.733333	0.733333	0.109799
10	0.882353	0.866667	0.133333	0.861607	0.723214	0.729730	0.103064
Average	0.859968	0.838065	0.161935	0.829781	0.659561	0.664646	0.125711

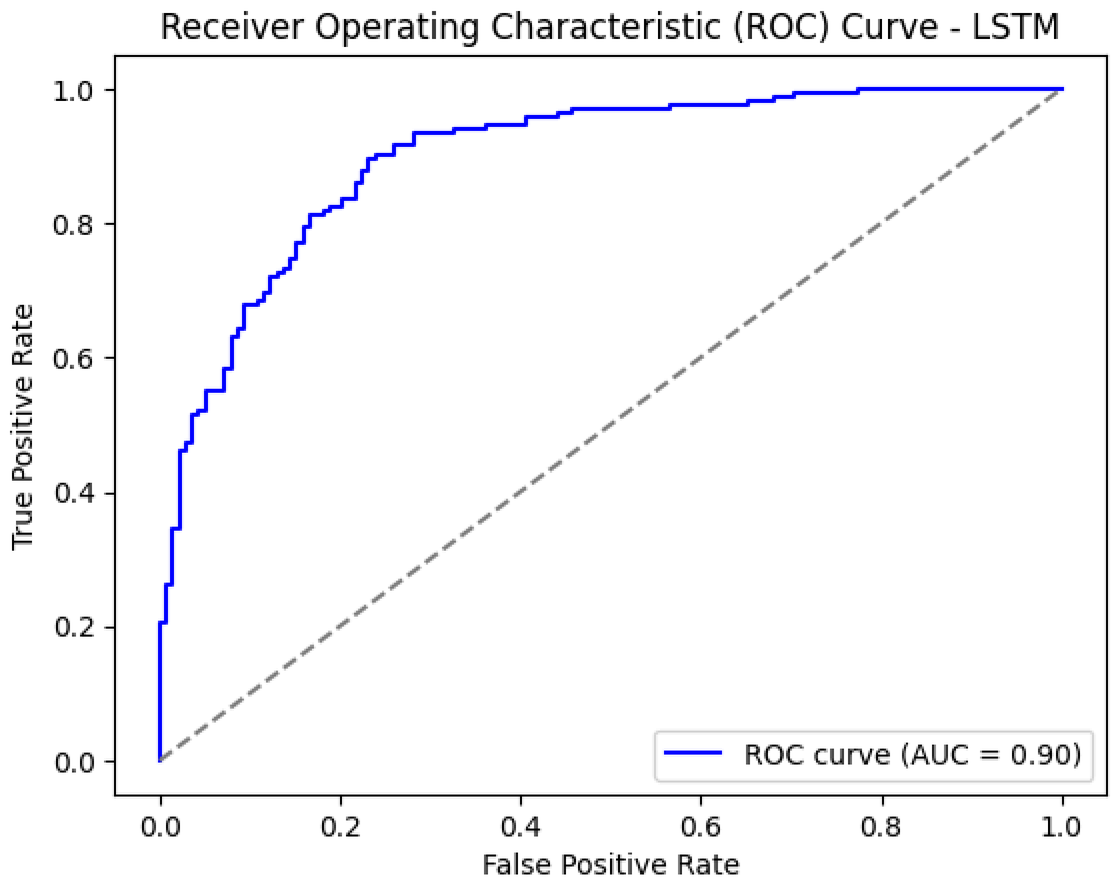
	Brier Skill Score	AUC
Fold		
1	0.374467	0.869748
2	0.709945	0.937500
3	0.391158	0.837719
4	0.504348	0.907407
5	0.559074	0.927602
6	0.444502	0.893519
7	0.298544	0.848889
8	0.506629	0.916667
9	0.565057	0.924444
10	0.586163	0.924107
Average	0.493989	0.898760

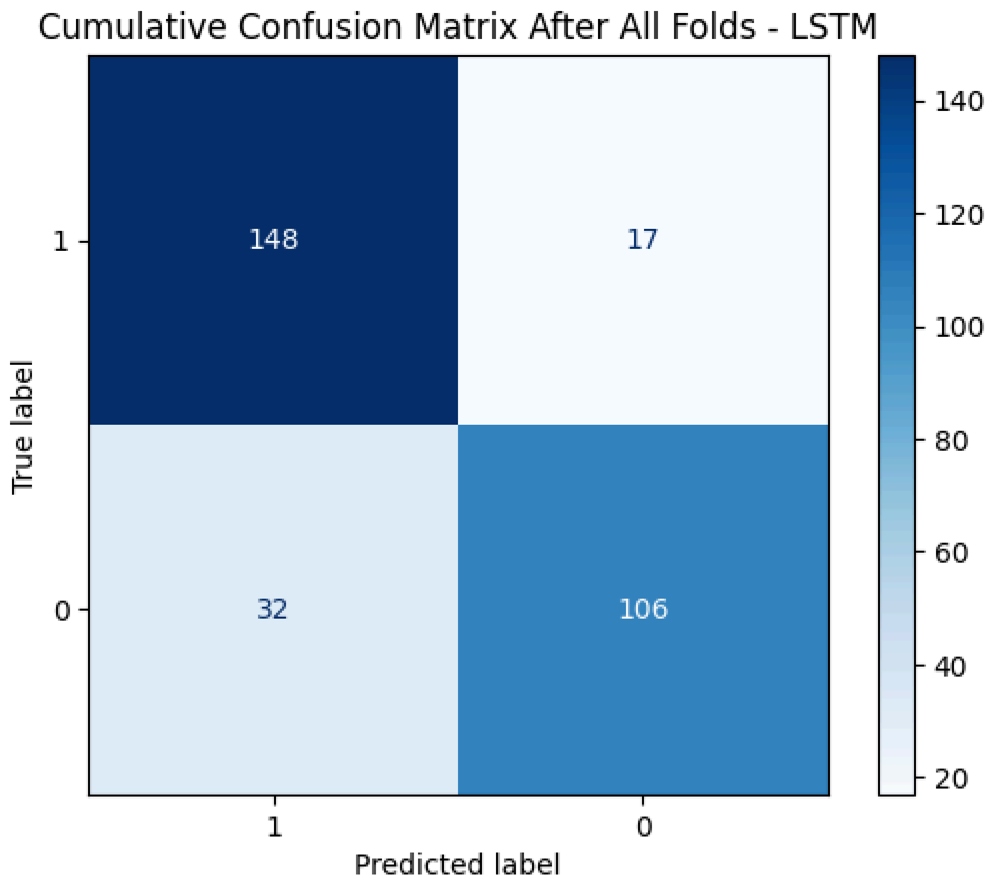

Receiver Operating Characteristic (ROC) Curve - Random Forest
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 0.90)


Cumulative Confusion Matrix After All Folds - Random Forest
140
25
30
108
True label
Predicted label
1
0
1
0
140
120
100
80
60
40


Receiver Operating Characteristic (ROC) Curve - SVM
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 0.90)


Cumulative Confusion Matrix After All Folds - SVM
True label
Predicted label
1
0
1
0
150
15
35
103
140
120
100
80
60
40
20


Receiver Operating Characteristic (ROC) Curve - LSTM
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
ROC curve (AUC = 0.90)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


Cumulative Confusion Matrix After All Folds - LSTM
True label
Predicted label
1
0
1
0
148
17
32
106
140
120
100
80
60
40
20

Results

Overall I think the best model is the Random Forest Classifier. After looking at all the metrics from each model through all folds they perform very similar to each other. In addition to this the Confusion Matrix for all the models are also very similar in terms of the amount of FP, FN, TP, and TN. And the last comparison through all folds all 3 models have a very similar ROC curve. So because of this I think the Random Forest Classifier is the best choice due to time. The random forest is able to execute significantly faster than either the Support Vector Machine or the LSTM model and there is no significant decline in any of the measured metrics. This was tested on a dataset with only 13 features and around 300 rows of data so it is possible that with more features one of the models may excel over the other two but based on the heart dataset being used with only 300 rows the Random Forest matches the other models performance and excels over the other two in execution time on such a small dataset so as the dataset grows the execution time difference will be even greater.

```
Random Forest Time: 0.05000805854797363
Support Vector Classifier Time: 0.84893798828125
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step
LSTM Time: 1.0399360656738281
```

As you can see in the screen shot when we timed each algorithm on a per fold basis we were able to find that the Random Forest was significantly faster than the other two.