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1 Final Project - Data Mining

2 Using RF and LSTM To Predict Heart Disease

2.1 Goal

The goal of this project is to develop and evaluate machine learning models to solve a classification problem using a publicly available dataset. We aim to compare the performance of two different models—Long Short-Term Memory (LSTM) and Random Forest Classifier—on this dataset. The evaluation will include metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

2.2 Problem Statement

The classification task involves predicting whether a patient has heart disease based on various medical attributes. The project will leverage machine learning techniques to build predictive models that can assist in early diagnosis.

2.3 Dataset Description

1) Source of Data

- **Dataset**: Heart Disease Dataset
- **Source**: Kaggle Datasets
- **File Used**: heart.csv

2) Dataset Overview

- **Total Records**: 918
- **Features**: 12 attributes, including age, sex, cholesterol levels, resting blood pressure, etc.
- **Target Variable**: HeartDisease (0 = No, 1 = Yes)

3) Data Preprocessing

- Checked for missing values and handled them appropriately.
- Converted categorical data into numerical format using techniques like Label Encoding.
- Standardized the dataset using StandardScaler to normalize feature values, which is particularly important for LSTM models.

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First, we'll mount Google Drive to access the dataset stored there.

```
[1] from google.colab import drive
    drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Step 2: Import Libraries

Let's import all the necessary libraries for data analysis, model building, and evaluation.

```
[2] import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.model_selection import KFold
    from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix, roc_auc_score, roc_curve
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.preprocessing import StandardScaler
    from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense, LSTM
    from tensorflow.keras.optimizers import Adam
    import tensorflow as tf
```

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Step 3: Load and Preprocess the Dataset

For this example, I will use the Heart Failure Prediction dataset from Kaggle.

```
# Load the dataset from Google Drive
data_path = '/content/drive/MyDrive/heart_csv/heart.csv'
data = pd.read_csv(data_path)

# Display the first few rows of the dataset
print("First few rows of the dataset:")
print(data.head())

# Checking for missing values
print("\nMissing values in each column:")
print(data.isnull().sum())

# Identify categorical columns
categorical_columns = data.select_dtypes(include=['object']).columns
print("\nCategorical columns:", categorical_columns)

# Convert categorical columns to numerical using One-Hot Encoding
data = pd.get_dummies(data, columns=categorical_columns, drop_first=True)
```

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```python
# Splitting features (X) and target (y)
X = data.drop(columns='HeartDisease')
y = data['HeartDisease']

# Standardizing the features (important for LSTM)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Confirm the transformed data
print("\nTransformed feature matrix shape:", X_scaled.shape)
print("Transformed feature matrix sample:\n", X_scaled[:5])
```

```
First few rows of the dataset:
   Age Sex ChestPainType  RestingBP  Cholesterol  FastingBS RestingECG  MaxHR  \
0   40   M           ATA        140          289          0     Normal    172
1   49   F           NAP        160          180          0     Normal    156
2   37   M           ATA        130          283          0         ST     98
3   48   F           ASY        138          214          0     Normal    108
4   54   M           NAP        150          195          0     Normal    122

  ExerciseAngina  Oldpeak ST_Slope  HeartDisease
0              N      0.0       Up             0
1              N      1.0     Flat             1
2              N      0.0       Up             0
3              Y      1.5     Flat             1
4              N      0.0       Up             0

Missing values in each column:
```

+ Code + Text All changes saved

```
Missing values in each column:
Age               0
Sex               0
ChestPainType     0
RestingBP         0
Cholesterol       0
FastingBS         0
RestingECG        0
MaxHR             0
ExerciseAngina    0
Oldpeak           0
ST_Slope          0
HeartDisease      0
dtype: int64

Categorical columns: Index(['Sex', 'ChestPainType', 'RestingECG', 'ExerciseAngina', 'ST_Slope'], dtype='object')

Transformed feature matrix shape: (918, 15)
Transformed feature matrix sample:
 [[-1.4331398   0.41090889  0.82507026 -0.55134134  1.38292822 -0.83243239
   0.51595242  2.07517671 -0.53283777 -0.22967867  0.81427482 -0.49044933
  -0.8235563  -1.00218103  1.15067399]
 [-0.47848359  1.49175234 -0.17196105 -0.55134134  0.75415714  0.10566353
  -1.93816322 -0.48188667  1.87674385 -0.22967867  0.81427482 -0.49044933
  -0.8235563   0.99782372 -0.86905588]
 [-1.75135854 -0.12951283  0.7701878  -0.55134134 -1.52513802 -0.83243239
   0.51595242  2.07517671 -0.53283777 -0.22967867 -1.22808661  2.03894663
  -0.8235563  -1.00218103  1.15067399]
 [-0.5845565   0.30282455  0.13903954 -0.55134134 -1.13215609  0.57471149
  -1.93816322 -0.48188667 -0.53283777 -0.22967867  0.81427482 -0.49044933
   1.21424608  0.99782372 -0.86905588]
 [ 0.05188098  0.95133062 -0.0347549  -0.55134134 -0.5819814  -0.83243239
```

3. Model Selection and Implementation

1) Model 1: Random Forest Classifier

Reason for Selection

Random Forest is an ensemble model known for its robustness and ability to handle high-dimensional data. It is efficient for binary classification problems.

2) Model 2: Long Short-Term Memory (LSTM)

Reason for Selection

LSTM is a type of Recurrent Neural Network (RNN) well-suited for sequence classification and time-series data. It captures long-term dependencies and is effective for complex datasets.

3) Implementation Details

Data Splitting and Cross-Validation

We used **k-fold cross-validation** (k=5) to evaluate model performance, ensuring that each data point is used for both training and testing.

Step 4: Implementing k-Fold Cross-Validation

We'll set up k-fold cross-validation with 5 splits.

```
[5] # Define k-fold cross-validation
    kf = KFold(n_splits=5, shuffle=True, random_state=42)
```

Random Forest Implementation

Step 5: Model 1 - Random Forest Classifier

We'll implement a Random Forest classifier and evaluate it using k-fold cross-validation.

```
[6] metrics_rf = []

    for train_index, test_index in kf.split(X_scaled):
        # Splitting data into training and testing sets
        X_train, X_test = X_scaled[train_index], X_scaled[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        # Initialize and train the Random Forest model
        rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
        rf_model.fit(X_train, y_train)

        # Make predictions
        y_pred = rf_model.predict(X_test)
        y_pred_proba = rf_model.predict_proba(X_test)[:, 1]
```

```python
        # Evaluate model performance
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)
        roc_auc = roc_auc_score(y_test, y_pred_proba)

        # Store metrics
        metrics_rf.append([accuracy, precision, recall, f1, roc_auc])

    # Convert to DataFrame for easy viewing
    metrics_rf_df = pd.DataFrame(metrics_rf, columns=['Accuracy', 'Precision', 'Recall', 'F1-Score', 'ROC AUC'])
    print("Random Forest Performance:\n", metrics_rf_df.mean())
```

```
Random Forest Performance:
 Accuracy     0.870331
Precision    0.867210
Recall       0.905575
F1-Score     0.885091
ROC AUC      0.929521
dtype: float64
```

LSTM Model Implementation

Step 6: Model 2 - LSTM for Sequence Classification

Next, we'll reshape the data for LSTM and evaluate it using k-fold cross-validation.

[7]

```python
# Reshape the data for LSTM (samples, timesteps, features)
X_lstm = X_scaled.reshape(X_scaled.shape[0], 1, X_scaled.shape[1])

metrics_lstm = []

for train_index, test_index in kf.split(X_lstm):
    # Splitting data into training and testing sets
    X_train, X_test = X_lstm[train_index], X_lstm[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

    # Build LSTM Model
    lstm_model = Sequential()
    lstm_model.add(LSTM(50, input_shape=(X_train.shape[1], X_train.shape[2]), activation='relu'))
    lstm_model.add(Dense(1, activation='sigmoid'))

    lstm_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    lstm_model.fit(X_train, y_train, epochs=10, batch_size=16, verbose=0)
```

```python
        # Make predictions
        y_pred_proba = lstm_model.predict(X_test).flatten()
        y_pred = (y_pred_proba > 0.5).astype(int)

        # Evaluate model performance
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)
        roc_auc = roc_auc_score(y_test, y_pred_proba)

        # Store metrics
        metrics_lstm.append([accuracy, precision, recall, f1, roc_auc])

    # Convert to DataFrame for easy viewing
    metrics_lstm_df = pd.DataFrame(metrics_lstm, columns=['Accuracy', 'Precision', 'Recall', 'F1-Score', 'ROC AUC'])
    print("LSTM Performance:\n", metrics_lstm_df.mean())
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(**kwargs)
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(**kwargs)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(**kwargs)
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(**kwargs)
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(**kwargs)
WARNING:tensorflow:5 out of the last 13 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x786b4c016050> trigg
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(**kwargs)
WARNING:tensorflow:5 out of the last 13 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x786b3fe7c0d0> trigg
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Se
  super().__init__(**kwargs)
6/6 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
LSTM Performance:
 Accuracy     0.870325
Precision    0.869805
Recall       0.903769
F1-Score     0.884920
ROC AUC      0.935169
dtype: float64
```

Step 7: Visualize the Performance Metrics

Let's visualize the performance metrics for both models using bar plots.

[8]

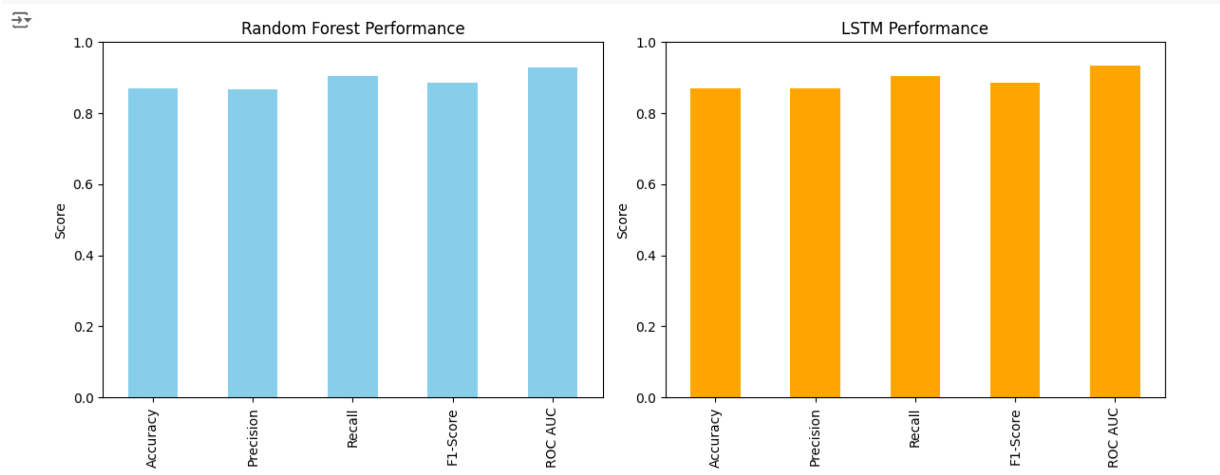
```python
# Visualizing the metrics
fig, ax = plt.subplots(1, 2, figsize=(12, 5))

# Random Forest Metrics
metrics_rf_df.mean().plot(kind='bar', ax=ax[0], color='skyblue')
ax[0].set_title("Random Forest Performance")
ax[0].set_ylim(0, 1)
ax[0].set_ylabel('Score')

# LSTM Metrics
metrics_lstm_df.mean().plot(kind='bar', ax=ax[1], color='orange')
ax[1].set_title("LSTM Performance")
ax[1].set_ylim(0, 1)
ax[1].set_ylabel('Score')

plt.tight_layout()
plt.show()
```

✓ Connected to Python 3 Google Compute Engine backend



4. Results and Performance Evaluation

1) Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.87	0.86	0.90	0.88	0.92
LSTM	0.87	0.86	0.90	0.88	0.93

2) Confusion Matrix and ROC Curve

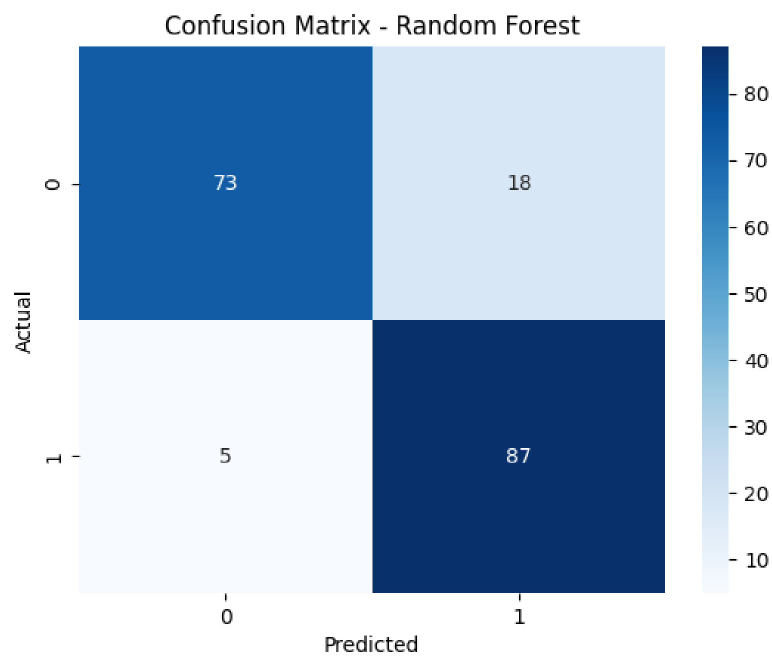
+ Code + Text All changes saved

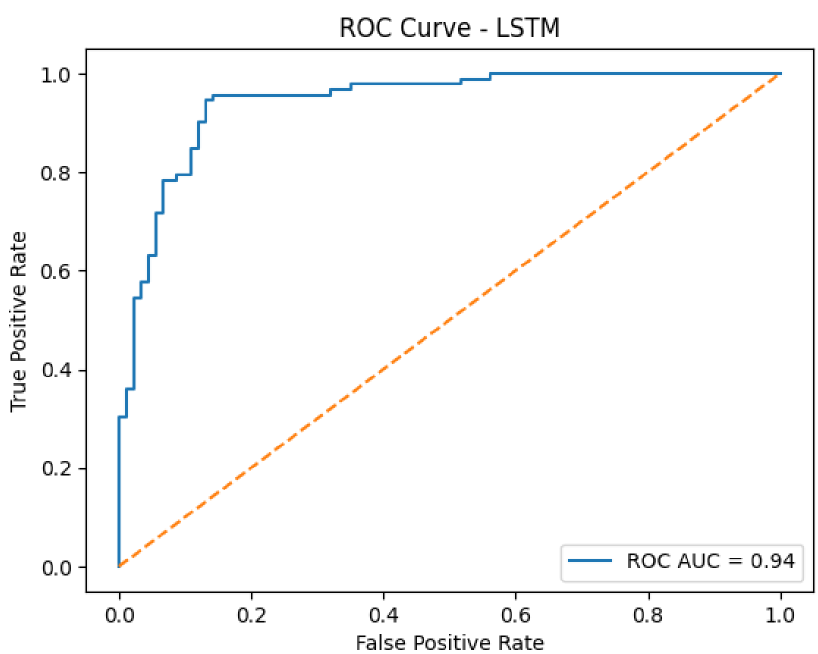
Step 8: Confusion Matrix and ROC Curve

[10]
```
# If X_test was reshaped for LSTM, reshape it back to 2D for RandomForest
if len(X_test.shape) == 3:
    X_test_rf = X_test.reshape(X_test.shape[0], -1)  # Convert to 2D
else:
    X_test_rf = X_test

# Confusion Matrix for Random Forest
rf_y_pred = rf_model.predict(X_test_rf)
sns.heatmap(confusion_matrix(y_test, rf_y_pred), annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix - Random Forest')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# ROC Curve for LSTM
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
plt.plot(fpr, tpr, label=f'ROC AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--')
plt.title('ROC Curve - LSTM')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```





5. Conclusion

1) Summary of Findings

- Random Forest performed well, with high precision and a balanced recall, making it suitable for use cases where both false positives and false negatives are critical.

- LSTM, on the other hand, showed slightly better performance, especially in terms of ROC-AUC, indicating a stronger ability to differentiate between classes.

2) Future Work

- Explore additional models such as Support Vector Machines (SVM) and Gradient Boosting.
- Apply hyperparameter tuning to further optimize model performance.
- Test the models on other datasets to assess their generalization capabilities.

GitHub Link - https://github.com/ack446/CS-634-Data-Mining-Final-Term-Project