Github link:
https://github.com/Hetvi-Patel-47/CS634-FinalTermProject

Steps to run python program

- Load diabetes.csv file from shared folder
- Run python program in the order shown below in Jupyter Notebook
- Import the necessary packages that are mentioned in the list below

Import

- Pandas
- Numpy
- Matplotlib.pyplot
- KNeighborsClassifier from Sklearn.neighbors
- RandomForestClassifier from sklearn.ensemble
- GridSearchCV from sklearn.model_selection
- StratifiedKFold from sklearn.model_selection
- Train_test_split from sklearn.model_selection
- Confusion_matrix from sklearn.metrics
- Brier_score_loss from sklearn.metrics
- Sequential from keras.models
- Dense from keras.layers
- LSTM from keras.layers

Reading CSV file and impute missing values

```
# Reading CSV file
diab = pd.read_csv('diabetes.csv')

# Impute missing values
def impute_missing_values(df):
    columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI',
               'DiabetesPedigreeFunction', 'Age']

    df[columns] = df[columns].replace(0, np.nan)
    df[columns] = df[columns].apply(lambda col: col.fillna(col.median()))

    return df

# Storing DF to a variable
diab = impute_missing_values(diab)

# Feature and label separation
features = diab.iloc[:, :-1]
labels = diab.iloc[:, -1]

print('Displaying Total Positive and Total Negative\n')
print('Number of Positive Outcomes: ', labels.value_counts()[0])
print('Number of Negative Outcomes : ', labels.value_counts()[1])
print('\n')
```

Output

```
Displaying Total Positive and Total Negative

Number of Positive Outcomes:  500
Number of Negative Outcomes :  268
```

Correlation Analysis between the Attributes

```
# Evaluating Correlations between Features
correlation_matrix = features.corr()
correlation_pairs = correlation_matrix.abs().unstack().sort_values(kind="quicksort", ascending=False)
correlation_pairs = correlation_pairs[correlation_pairs < 1.0]
highest_corr_pairs = correlation_pairs.head(4)

print('Pairs that are heighest correlated: \n')
print(highest_corr_pairs.round(decimals=2).T)
print('\n')
```

Output

```
Pairs that are heighest correlated:

SkinThickness  BMI              0.54
BMI            SkinThickness    0.54
Pregnancies    Age              0.52
Age            Pregnancies      0.52
dtype: float64
```

Note: Two pairs are highly correlated

- SkinThickness and BMI

- Pregnancies and Age

Splitting Data for Training and Test dataset

```
# Method to split the data into training and test data set.
def split_data(features, labels, test_size=0.1, random_state=21, stratify=None):
    return train_test_split(features, labels, test_size=test_size, random_state=random_state,
                            stratify=stratify)

features_train_all, features_test_all, labels_train_all, labels_test_all = split_data(features, labels,
                                                                                       stratify=labels)

# Method to reset the each dataset
def reset_index(datasets):
    for dataset in datasets:
        dataset.reset_index(drop=True, inplace=True)

reset_index([features_train_all, features_test_all, labels_train_all, labels_test_all])

# This standardization ensures that the scale of the features are balanced for the model's performance
# Standardize features for training set
features_train_all_std = (features_train_all - features_train_all.mean()) / features_train_all.std()

# Standardize features for testing set
features_test_all_std = (features_test_all - features_test_all.mean()) / features_test_all.std()
```

Note: Data set is split into training and test dataset. Standardizing features for training and testing set to make sure the values are balanced to get good performance.

Metric Calculation

```
def calculate_metrics(conf_matrix):
    TP, FN = conf_matrix[0][0], conf_matrix[0][1]
    FP, TN = conf_matrix[1][0], conf_matrix[1][1]

    TPR = TP / (TP + FN)
    TNR = TN / (TN + FP)
    FPR = FP / (TN + FP)
    FNR = FN / (TP + FN)
    Precision = TP / (TP + FP)
    F1_measure = 2 * TP / (2 * TP + FP + FN)
    Accuracy = (TP + TN) / (TP + FP + FN + TN)
    Error_rate = (FP + FN) / (TP + FP + FN + TN)
    # Balanced Accuracy
    BACC = (TPR + TNR) / 2
    # True Skill Statistics
    TSS = TPR - FPR
    # Heidke Skill Score
    HSS = 2 * (TP * TN - FP * FN) / ((TP + FN) * (FN + TN) + (TP + FP) * (FP + TN))

    return [TP, TN, FP, FN, TPR, TNR, FPR, FNR, Precision, F1_measure, Accuracy, Error_rate, BACC, TSS, HSS]
```

Note: This method calculates TP, FN, FP, TN, TPR, TNR, FPR, FNR, Precision, F1_measure, Accuracy, Error_rate, BACC, TSS, HSS by using the formulas from Module 8

Evaluating Performance of ML Model

```
def get_metrics(model, x_train, x_test, y_train, y_test, LSTM_flag):
    metrics = []

    # Convert data to numpy array
    feature_train, feature_test, label_train, label_test = map(np.array, [x_train, x_test, y_train, y_test])

    # if LSTM flag is true
    if LSTM_flag:
        # Reshape data for LSTM model
        x_train_reshaped = feature_train.reshape(len(feature_train), feature_train.shape[1], 1)
        x_test_reshaped = feature_test.reshape(len(feature_test), feature_test.shape[1], 1)

        model.fit(x_train_reshaped, label_train, epochs=50, validation_data=(x_test_reshaped,
                                                                              label_test), verbose=0)
        lstm_scores = model.evaluate(x_test_reshaped, label_test, verbose=0)
        predict_prob = model.predict(x_test_reshaped)
        pred_labels = (predict_prob > 0.5).astype(int)
        conf_matrix = confusion_matrix(label_test, pred_labels, labels=[1, 0])
        lstm_brier_score = brier_score_loss(label_test, predict_prob)
        metrics.extend(calculate_metrics(conf_matrix))
        metrics.extend([lstm_brier_score, lstm_scores[1]])

    # if LSTM flag is false
    else:
        model.fit(feature_train, label_train)
        conf_matrix = confusion_matrix(label_test, model.predict(feature_test), labels=[1, 0])
        model_brier_score = brier_score_loss(label_test, model.predict_proba(feature_test)[:, 1])
        metrics.extend(calculate_metrics(conf_matrix))
        metrics.extend([model_brier_score, model.score(feature_test, label_test)])

    return metrics
```

Note: This method trains models by training data and evaluates using the test data. This includes training the LSTM model as well.

Classification Algorithm Choice

Classification algorithms

- KNN

```
# KNN
# KNN parameters for grid search
knn_parameters = {"n_neighbors": range(1, 16)}

knn_model = KNeighborsClassifier()

# Grid search with cross-validation
knn_cv = GridSearchCV(knn_model, knn_parameters, cv=10, n_jobs=-1)
knn_cv.fit(features_train_all_std, labels_train_all)

print('KNN Parameter: ', knn_cv.best_params_['n_neighbors'])
print('\n')
```

```
KNN Parameter:  15
```

- Random Forest

```python
# RF (Random Forest)
# RF parameters for grid search
param_grid_rf = {"n_estimators": range(10, 110, 10), "min_samples_split": range(2, 12, 2)}
rf_model = RandomForestClassifier()

# Grid search with cross-validation
rf_cv = GridSearchCV(estimator=rf_model, param_grid=param_grid_rf, cv=10, n_jobs=-1)
rf_cv.fit(features_train_all_std, labels_train_all)

# Values for 'min_samples_split' and 'n_estimators'
split = rf_cv.best_params_['min_samples_split']
estimators = rf_cv.best_params_['n_estimators']
print('Random Forest Parameter: ', rf_cv.best_params_)
print('\n')
```

```
Random Forest Parameter:  {'min_samples_split': 10, 'n_estimators': 90}
```

Deep Learning Algorithm

- LSTM (Long Short Term Memory)

```python
# LSTM (Long Short Term Memory)
def get_LSTM():
    lstm_model = Sequential()
    lstm_model.add(LSTM(64, activation='relu', batch_input_shape=(None, 8 ,1), return_sequences=False))
    lstm_model.add(Dense(1, activation='sigmoid'))
    lstm_model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    return lstm_model
```

Implementation of 10-fold Stratified Cross-Validation

```
kFold = StratifiedKFold(n_splits=10, shuffle=True, random_state=21)

# Metric columns
metric_columns = ['TP', 'TN', 'FP', 'FN', 'TPR', 'TNR', 'FPR', 'FNR', 'Precision', 'F1_measure', 'Accuracy',
                  'Error_rate', 'BACC', 'TSS', 'HSS', 'Brier_score', 'Acc_by_package_fn']

# List for each algorithm
knn_metrics_list, rf_metrics_list, lstm_metrics_list = [], [], []

# for loop for 10-fold iterations
for iter_num, (train_index, test_index) in enumerate(kFold.split(features_train_all_std,
                                                                 labels_train_all), start=1):
    # KNN model
    knn_model = KNeighborsClassifier(n_neighbors=neighbors)
    # RF model
    rf_model = RandomForestClassifier(min_samples_split=split, n_estimators=estimators)
    # LSTM model
    lstm_model = get_LSTM()

    # Spliting data into training and testing data sets
    features_train, features_test = features_train_all_std.iloc[train_index, :],
        features_train_all_std.iloc[test_index, :]
    labels_train, labels_test = labels_train_all[train_index], labels_train_all[test_index]

    knn_metrics = get_metrics(knn_model, features_train, features_test, labels_train, labels_test, 0)
    rf_metrics = get_metrics(rf_model, features_train, features_test, labels_train, labels_test, 0)
    lstm_metrics = get_metrics(lstm_model, features_train, features_test, labels_train, labels_test, 1)

    knn_metrics_list.append(knn_metrics)
    rf_metrics_list.append(rf_metrics)
    lstm_metrics_list.append(lstm_metrics)

    metrics_all_df = pd.DataFrame([knn_metrics, rf_metrics, lstm_metrics], columns=metric_columns,
                                  index=['KNN', 'RF', 'LSTM'])
    print('\nMetrics for all Algoritm in Iteration {}\n'.format(iter_num))
    display(metrics_all_df.round(decimals=2).T)
    print('\n')
```

Note: Training models and getting metrics for all 3 algorithms. Prints 10 iterations with each matrix for KNN, RF and LSTM.

Printing Metric for each iteration and Algorithm in Tabular format

```
# Define iteration indices
metric_index_df = [f'iter{i}' for i in range(1, 11)]

# Create DataFrames for each algorithm's metrics
metrics_dfs = {
    'KNN': pd.DataFrame(knn_metrics_list, columns=metric_columns, index=metric_index_df),
    'RF': pd.DataFrame(rf_metrics_list, columns=metric_columns, index=metric_index_df),
    'LSTM': pd.DataFrame(lstm_metrics_list, columns=metric_columns, index=metric_index_df)
}

# Print metrics for each algorithm
for algo_name, metrics_df in metrics_dfs.items():
    print(f"\nMetrics for Algorithm {algo_name}:\n")
    display(metrics_df.round(decimals=2).T)
```

Output

KNN

```
Metrics for Algorithm KNN:
```

	iter1	iter2	iter3	iter4	iter5	iter6	iter7	iter8	iter9	iter10
TP	14.00	12.00	11.00	13.00	7.00	16.00	16.00	14.00	15.00	16.00
TN	39.00	38.00	34.00	41.00	41.00	40.00	38.00	40.00	40.00	38.00
FP	6.00	7.00	11.00	4.00	4.00	5.00	7.00	5.00	5.00	7.00
FN	11.00	12.00	13.00	11.00	17.00	8.00	8.00	10.00	9.00	8.00
TPR	0.56	0.50	0.46	0.54	0.29	0.67	0.67	0.58	0.62	0.67
TNR	0.87	0.84	0.76	0.91	0.91	0.89	0.84	0.89	0.89	0.84
FPR	0.13	0.16	0.24	0.09	0.09	0.11	0.16	0.11	0.11	0.16
FNR	0.44	0.50	0.54	0.46	0.71	0.33	0.33	0.42	0.38	0.33
Precision	0.70	0.63	0.50	0.76	0.64	0.76	0.70	0.74	0.75	0.70
F1_measure	0.62	0.56	0.48	0.63	0.40	0.71	0.68	0.65	0.68	0.68
Accuracy	0.76	0.72	0.65	0.78	0.70	0.81	0.78	0.78	0.80	0.78
Error_rate	0.24	0.28	0.35	0.22	0.30	0.19	0.22	0.22	0.20	0.22
BACC	0.71	0.67	0.61	0.73	0.60	0.78	0.76	0.74	0.76	0.76
TSS	0.43	0.34	0.21	0.45	0.20	0.56	0.51	0.47	0.51	0.51
HSS	0.45	0.36	0.22	0.49	0.23	0.57	0.52	0.50	0.53	0.52
Brier_score	0.17	0.17	0.21	0.16	0.19	0.13	0.15	0.15	0.15	0.14
Acc_by_package_fn	0.76	0.72	0.65	0.78	0.70	0.81	0.78	0.78	0.80	0.78

RF

```
Metrics for Algorithm RF:
```

	iter1	iter2	iter3	iter4	iter5	iter6	iter7	iter8	iter9	iter10
TP	17.00	11.00	12.00	18.00	10.00	17.00	16.00	13.00	17.00	18.00
TN	37.00	39.00	34.00	41.00	38.00	40.00	35.00	39.00	34.00	41.00
FP	8.00	6.00	11.00	4.00	7.00	5.00	10.00	6.00	11.00	4.00
FN	8.00	13.00	12.00	6.00	14.00	7.00	8.00	11.00	7.00	6.00
TPR	0.68	0.46	0.50	0.75	0.42	0.71	0.67	0.54	0.71	0.75
TNR	0.82	0.87	0.76	0.91	0.84	0.89	0.78	0.87	0.76	0.91
FPR	0.18	0.13	0.24	0.09	0.16	0.11	0.22	0.13	0.24	0.09
FNR	0.32	0.54	0.50	0.25	0.58	0.29	0.33	0.46	0.29	0.25
Precision	0.68	0.65	0.52	0.82	0.59	0.77	0.62	0.68	0.61	0.82
F1_measure	0.68	0.54	0.51	0.78	0.49	0.74	0.64	0.60	0.65	0.78
Accuracy	0.77	0.72	0.67	0.86	0.70	0.83	0.74	0.75	0.74	0.86
Error_rate	0.23	0.28	0.33	0.14	0.30	0.17	0.26	0.25	0.26	0.14
BACC	0.75	0.66	0.63	0.83	0.63	0.80	0.72	0.70	0.73	0.83
TSS	0.50	0.32	0.26	0.66	0.26	0.60	0.44	0.41	0.46	0.66
HSS	0.50	0.35	0.26	0.67	0.28	0.61	0.44	0.43	0.45	0.67
Brier_score	0.17	0.17	0.22	0.14	0.19	0.12	0.16	0.18	0.16	0.12
Acc_by_package_fn	0.77	0.72	0.67	0.86	0.70	0.83	0.74	0.75	0.74	0.86

LSTM

```
Metrics for Algorithm LSTM:
```

	iter1	iter2	iter3	iter4	iter5	iter6	iter7	iter8	iter9	iter10
TP	13.00	13.00	9.00	11.00	12.00	17.00	15.00	13.00	17.00	15.00
TN	37.00	32.00	38.00	43.00	39.00	35.00	34.00	40.00	37.00	39.00
FP	8.00	13.00	7.00	2.00	6.00	10.00	11.00	5.00	8.00	6.00
FN	12.00	11.00	15.00	13.00	12.00	7.00	9.00	11.00	7.00	9.00
TPR	0.52	0.54	0.38	0.46	0.50	0.71	0.62	0.54	0.71	0.62
TNR	0.82	0.71	0.84	0.96	0.87	0.78	0.76	0.89	0.82	0.87
FPR	0.18	0.29	0.16	0.04	0.13	0.22	0.24	0.11	0.18	0.13
FNR	0.48	0.46	0.62	0.54	0.50	0.29	0.38	0.46	0.29	0.38
Precision	0.62	0.50	0.56	0.85	0.67	0.63	0.58	0.72	0.68	0.71
F1_measure	0.57	0.52	0.45	0.59	0.57	0.67	0.60	0.62	0.69	0.67
Accuracy	0.71	0.65	0.68	0.78	0.74	0.75	0.71	0.77	0.78	0.78
Error_rate	0.29	0.35	0.32	0.22	0.26	0.25	0.29	0.23	0.22	0.22
BACC	0.67	0.63	0.61	0.71	0.68	0.74	0.69	0.72	0.77	0.75
TSS	0.34	0.25	0.22	0.41	0.37	0.49	0.38	0.43	0.53	0.49
HSS	0.35	0.25	0.24	0.46	0.39	0.47	0.37	0.46	0.53	0.51
Brier_score	0.18	0.19	0.22	0.16	0.18	0.16	0.19	0.19	0.16	0.13
Acc_by_package_fn	0.71	0.65	0.68	0.78	0.74	0.75	0.71	0.77	0.78	0.78

Average Metrics for Each Algorithm

```
# Calculate the average metrics for each algorithm
avg_metrics_dfs = {
    'KNN': metrics_dfs['KNN'].mean(),
    'RF': metrics_dfs['RF'].mean(),
    'LSTM': metrics_dfs['LSTM'].mean()
}

# Create a DataFrame with the average performance for each algorithm
avg_performance_df = pd.DataFrame(avg_metrics_dfs, index=metric_columns)

# Display the average performance for each algorithm
print("Average Performance for Each Algorithm:")
display(avg_performance_df.round(decimals=2))
print('\n')
```

Output:

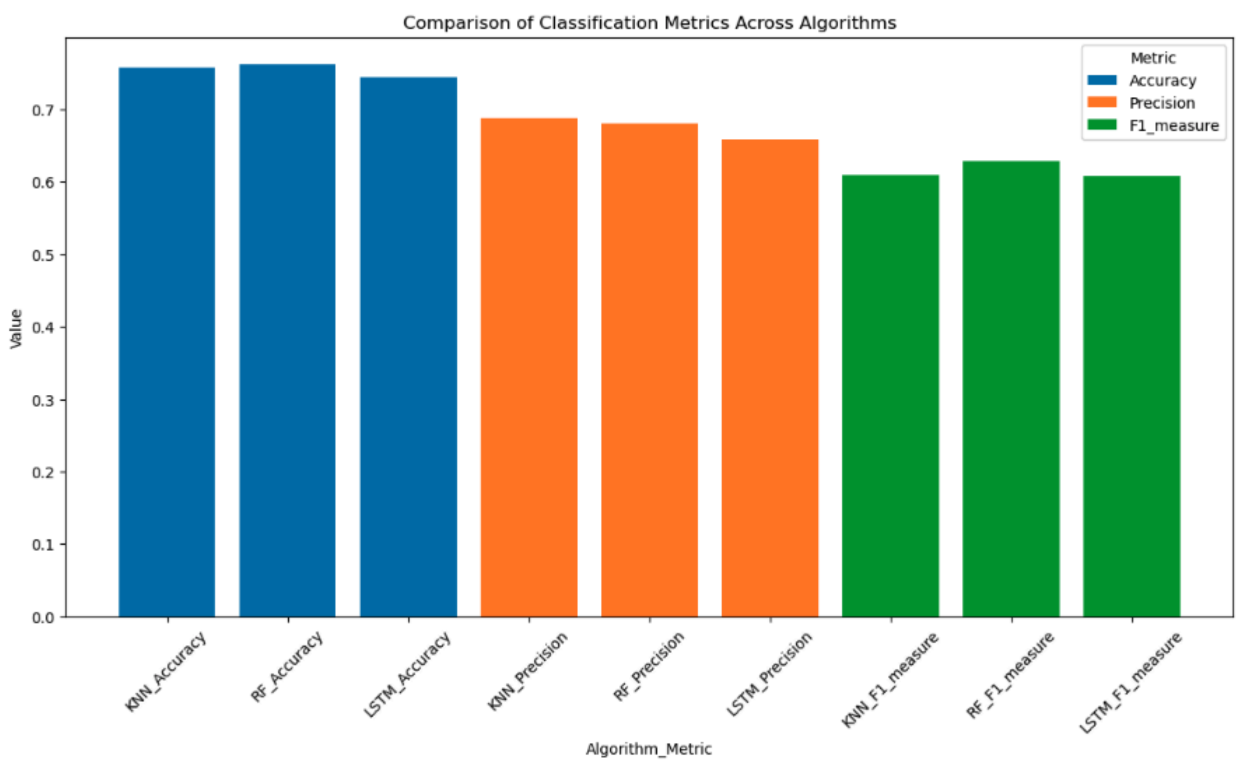
```
Average Performance for Each Algorithm:
```

	KNN	RF	LSTM
TP	13.40	14.90	13.50
TN	38.90	37.80	37.40
FP	6.10	7.20	7.60
FN	10.70	9.20	10.60
TPR	0.56	0.62	0.56
TNR	0.86	0.84	0.83
FPR	0.14	0.16	0.17
FNR	0.44	0.38	0.44
Precision	0.69	0.68	0.65
F1_measure	0.61	0.64	0.59
Accuracy	0.76	0.76	0.74
Error_rate	0.24	0.24	0.26
BACC	0.71	0.73	0.70
TSS	0.42	0.46	0.39
HSS	0.44	0.47	0.40
Brier_score	0.16	0.16	0.18
Acc_by_package_fn	0.76	0.76	0.74

Graph Presentation for all 3 algorithms

```python
# Extracting data for the bar plot
metrics = ['Accuracy', 'Precision', 'F1_measure']
algorithms = ['KNN', 'RF', 'LSTM']
data = {
    'Metric': [],
    'Algorithm': [],
    'Value': []
}

for metric in metrics:
    for algo in algorithms:
        data['Metric'].append(metric)
        data['Algorithm'].append(algo)
        data['Value'].append(avg_performance_df.loc[metric, algo])

# Create a DataFrame for plotting
comparison_df = pd.DataFrame(data)

# Plotting
plt.figure(figsize=(14, 7))
for metric in metrics:
    subset = comparison_df[comparison_df['Metric'] == metric]
    plt.bar(subset['Algorithm'] + '_' + metric, subset['Value'], label=metric)

plt.xlabel('Algorithm_Metric')
plt.ylabel('Value')
plt.title('Comparison of Classification Metrics Across Algorithms')
plt.legend(title='Metric')
plt.xticks(rotation=45)
plt.show()
```

Output:



Conclusion

Based on the performance metrics, we observed that:

- Random Forest gives highest accuracy, which makes it the most efficient model for this classification problem. So, It is recommended to use Random Forest.