Course: 634
Subject: Final Project
Topic: 3 Algorithm Comparison
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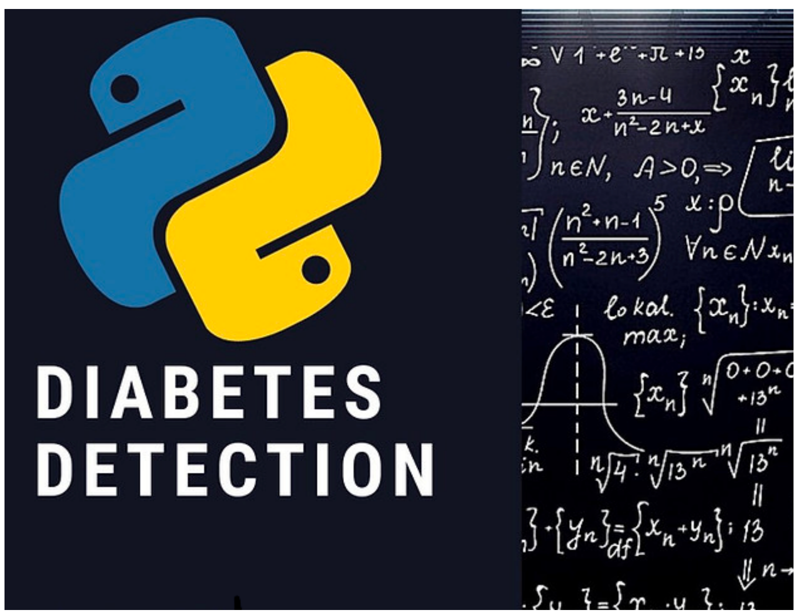
3 Algorithms: Random Forest, KNN, LSTM



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Introduction

The objective of the project is to apply different learning models on the same dataset and analyze the result. ROC curve after the training and testing will be used to determine the test result. The project aims to present Supervised Data Mining Classification using three different algorithms. First two algorithms used are Random Forest and KNN classification. For the deep learning option, LSTM is the chosen algorithm.

Random Forest

Random Forest is an algorithm that breaks down the classification problem into fundamental blocks using which decisions are made. The typical steps involved in following a Random Forest algorithm are, divide the data into train data and test data, find the Gini Impurity of each attribute column against the label of the dataset, pick the column with highest gini value, ff an attribute has n different categories, then the data must be split 2^{n-1}-1, keep growing n trees. The output of Random Forest algorithms depends on the result of most trees.

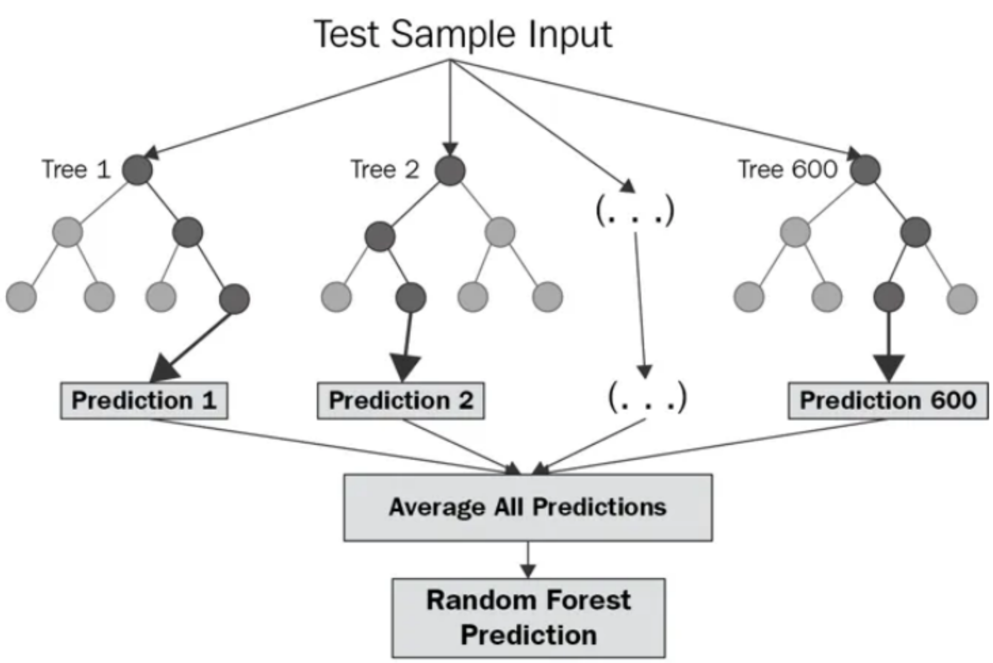

Figure 1: Random Forest Classification(Source1)

KNN (K-Nearest Neighbor)

This algorithm takes a k value which is provided by the data scientist. This number k represents the number of neighbors that will be utilized to compute the solution. Typically, lower values of k are taken (2, 3, 4 etc.) so that it generates more neighboring groups. The algorithm applies labels to datapoints based on the rule of majority classification for nearest neighbors. The K nearest neighbors are calculated using Euclidean distance.

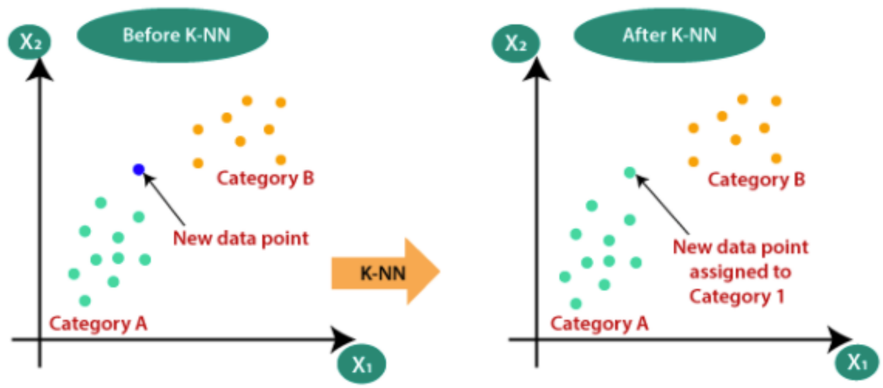

Figure 2: K-Nearest Neighbor Classification (Source2javapoint)

Long short term memory (LSTM)

LSTM is a recurrent neural network variant with long term memory. A lot of times LSTM is good with dataset that has a time component. This model has 3 gates, input, output, and keep gate where data is maintained.

- The “Write” gate takes care of entering the data into the information cell
- The “Read” gate ensures the data is sent back to the recurrent network
- The “Forget” gate makes sure to maintain and notify data that is stored in the information cell

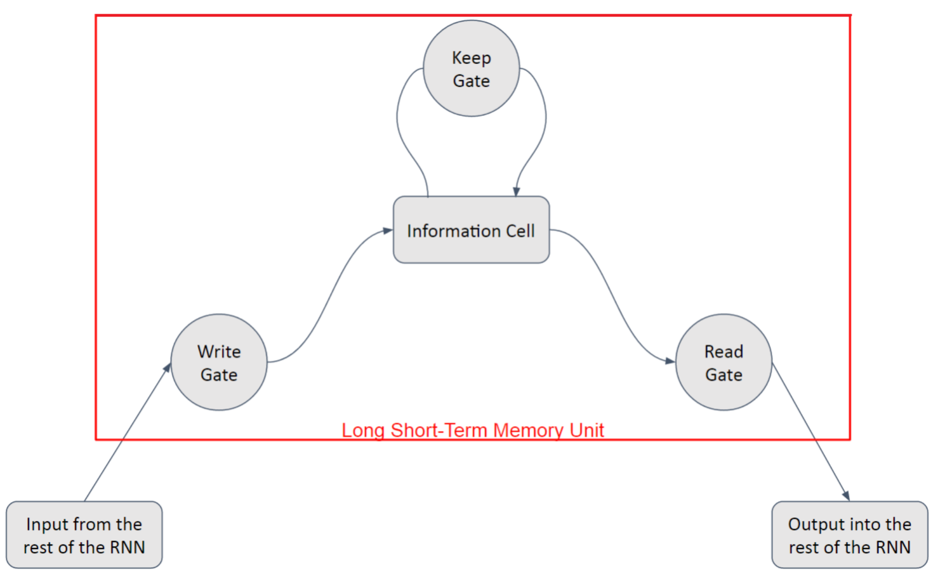

Figure 3: LSTM (source3lstm)

Assumption

- Although I have taken necessary steps to handle missing data, it is assumed that the data being used is valid and appropriate for all three algorithms
- For the KNN algorithm, I assumed the value of k = 7

Requirement

Software

Python3, https://colab.research.google.com/ was used to build and execute the code.
Pyenv environments are in built in the system.

Libraries used:

- mlxtend.plotting
- numpy
- pandas
- matplotlib.pyplot
- sklearn.model_selection
- sklearn.neighbors
- RandomForestClassifier
- KNeighborsClassifier
- RandomForestRegressor
- Export_graphviz
- Metrics
- Accuracy_score
- confusion_matrix
- plot_roc_curve
- SVC
- Seaborn
- TensorFlow
- Keras
- MinMaxScaler
- Sequential()

Hardware

MacBook Pro, Apple M1chip, MacOS 12.0.1

List of Source code Files

- Mathew_Sheethal_634Option1.ipynb
- mathew_sheethal_634option1.py

Compile the source Code

Follow these steps to compile the ipynb file,

- Go to the google collab link here: https://colab.research.google.com/drive/1vne05liWb6hsMCkkRltfapYEh348aSdq#scrollTo=d66_si_wE9pv
- Hit connect.
- You will notice diabetes.csv pre uploaded under files

How to run the Application

To run the application, follow these steps,

- Open the google collab link listed above
- Click on RunTime located on the task bar
- Select Run All

Dataset

Dataset is taken from the "Pima Indians Diabetes Database" (Dataset). Name of the data file: diabetes.csv. The dataset is from National Institute of Diabetes and Digestive and Kidney diseases. Using the dataset, and analyzing it, it can predict whether a patient has diabetes. It must be noted that the data is taken from Pima Indian Heritage women only. The attributes that contribute to whether the person does or does not have diabetes are Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Age and Diabetes Pedigree Function which are named appropriately as seen in Fig. 3. The label of the data is the 'Outcome' column which has values of 0 or 1 indicating no diabetes, and yes diabetes respectively. All three algorithms used the same dataset "diabetes.csv".

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Figure 4: Diabetes dataset top 5 rows

Data Clean Up

The anomalies in the data be determined using the describe() method. This method creates statistics summary of the tendency, dispersion and shape of a dataset distribution excluding NaN values. This method is used as a part of ensuring that only valid numeric values will be present in the final dataset that will separated as both training data and testing data, in order to be delivered as input to all the three classification algorithms

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

Figure 5: Dataset Anomalies

It can be found that Blood Pressure of 0, and Skin thickness of 0 and other 0.00 values are an anomaly. The only way to get a 0 for these metrics are if the person does not exist(null). To mitigate this the dataset has been altered to replace 0 with Nan values. Nan values are Not a Number special values in datafram or numpy arrays. Therefore, we mark 0 as data missing. Skin Thickness and Insulin as 0.00 does not make sense. If skin thickness is 0 or insulin is 0 then it does not make sense that the person is alive. The minimum is 0.00 for several of these attributes and that should be data that can be eliminated as it will skew our results down heavily.

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148.0	72.0	35.0	125.0	33.6	0.627	50	1
1	1	85.0	66.0	29.0	125.0	26.6	0.351	31	0
2	8	183.0	64.0	29.0	125.0	23.3	0.672	32	1
3	1	89.0	66.0	23.0	94.0	28.1	0.167	21	0
4	0	137.0	40.0	35.0	168.0	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101.0	76.0	48.0	180.0	32.9	0.171	63	0
764	2	122.0	70.0	27.0	125.0	36.8	0.340	27	0
765	5	121.0	72.0	23.0	112.0	26.2	0.245	30	0
766	1	126.0	60.0	29.0	125.0	30.1	0.349	47	1
767	1	93.0	70.0	31.0	125.0	30.4	0.315	23	0

768 rows × 9 columns

Figure 6: (a) Before cleaning up the data, (b) After cleaning the NaN and 0 values in Insulin column

Split the data into test set and training set. The Need to split it before applying model is because if training set includes test set, that would mean the model would return 100% accuracy, but that defeats the purpose of analyzing and learning data. For the Random Forest case and KNN, and LTSM data was split to 25% test and 75% training set.

Implementation and Result

AUC scores from Random Forest Model and KNN Model are 83% and 62% respectively. For Random Forest training, it can be seen that the training of ROC curve is more diagonal and less curvy than that of KNN model with AUC lower than the RF model. KNN model has reached its almost stabilized form at 62% as represented by the graph. In my case, it was proven that Random Forest was more accurate from the AUC score. The column Outcome determines the final results and therefore can be used for labelling the dataset as left pile and right pile.

Random Forest Result

After the dataset was split into trainingAttributes, testAttributes, Train Label and Test Label. randomModel was created using RandomForestClassifier with 100 number of trees. This n_estimator number was provided by me at random. The randomModel was applied on the sets: trainingAttributesSet, trainingLabelSet. Once the training is done, a prediction was done on test set using randModel.predict() function.

```
randModel = RandomForestClassifier(n_estimators=100,random_state=0)
randModel.fit(train_attributes, trainLabel)
predictedTest = randModel.predict(test_attributes)
```

Figure 7: Applying RandomForestClassifier on dataset and training it, and predicting against Test set

The accuracy of the randomModel was determined as 62%. Below you will find the tree with depth reduced to 3 levels instead of the 100-branch tree.

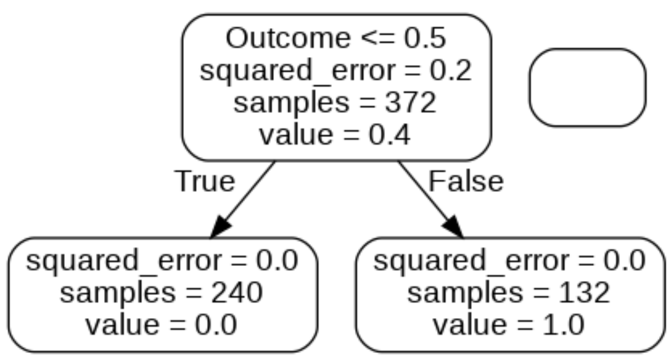

Figure 8: RandomForestTree with depth reduced to 3 levels.

Receiver Operating Characteristic Cruve(ROC) tells us how good model can differentiate between two classes. In our case, if the patient has diabetes or not. When the curve is lower it means it is able to determine the difference between diabetes and no diabetes. Figure below shows the ROC curve is slow and that means accuracy of prediction being high.

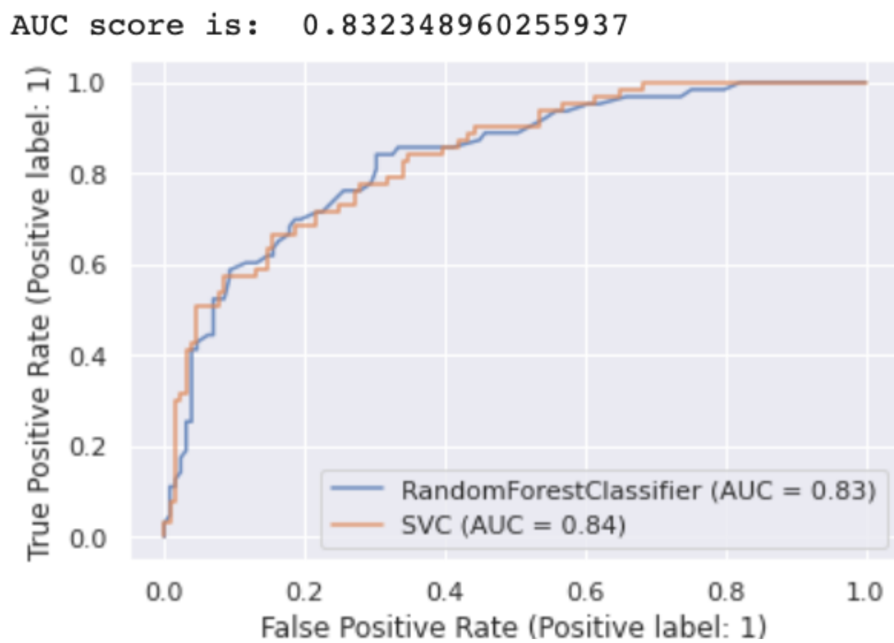

Figure 9: ROC curve of randomForestModel, at KFold=2

KNN Result

KNN finds the Euclidean distance between neighboring datapoints, therefore it is important to normalize the data to a range such that the Euclidean distance won't be skewed. In its original data, if some point is far away(an anomaly) from its neighbors, and if weightage is not calculated correctly, that could skew the distance calculation significantly.

Using the 'KNegihborsClassifier' library, KNN model is applied to the 'trainingAttributes' and 'trainingLabel' that was created earlier when cleaning up the dataset. After training on 75% of the data the max score is 77.64% and k=4,6. I arbitrarily chose k=7 for knn.

The following lines of code trained the dataset with knn model

```
for i in range(1,7):
  knn = KNeighborsClassifier(i)
  knn.fit(trainAttr, trainLabel)
```

```
[20] p = sns.lineplot(range(1,7), train_calc, marker='*', label='Train Calculated')
     p = sns.lineplot(range(1,7), test_calc, marker='o', label='Test Calculated')
```

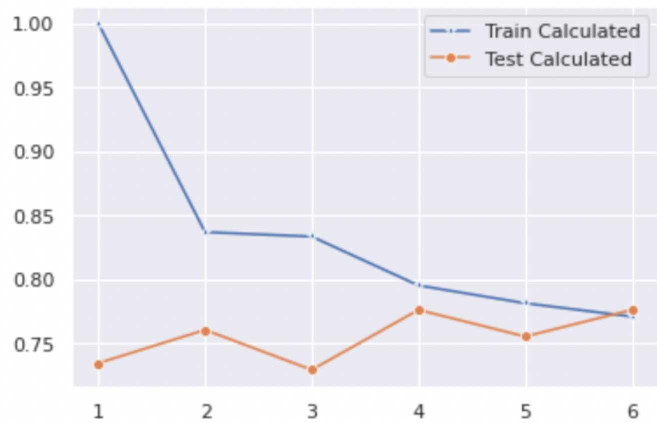

Figure 10: KNN Visualized comparison of score on trained dataset vs test dataset

When the model is run on the labeled data, Euclidean distance is calculated between points, and point is classified into the same class as neighbors. It is important to normalize data so the Euclidean distance wont show skewed results. Hence over-fitting and underfitting problems can be well avoided with cross validation techniques

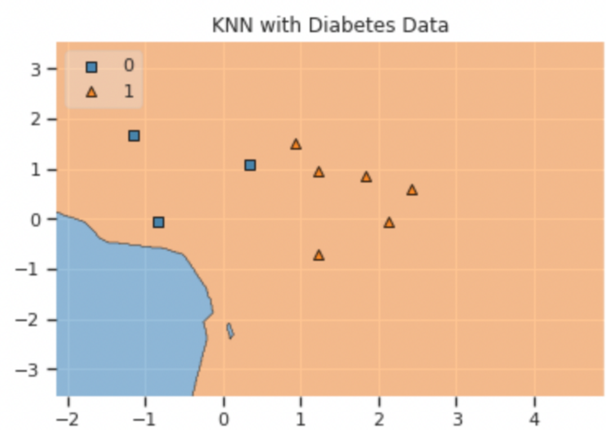

Figure 11: KNN model neighbors with k=7

Now we can run confusion matrix on the model. It takes into account predicted values vs actual values. The TN, FP, FN and TP can be found in the matrix below. Confusion matrices represent true labels on rows and predicted label on columns. Diagonal values represent the percent of predicted label matching true label. At KFold=2 you will find support of TN is 88, FP is 33, FN is 35, and TP is 36. The accuracy of the KNN model was determined as 77% at this KFold. Figure below shows, AUC value is 0.62 and the curve is higher for KNN model.

```
[88 33 35 36] (4,)
AUC score is:  0.617157490396927
```

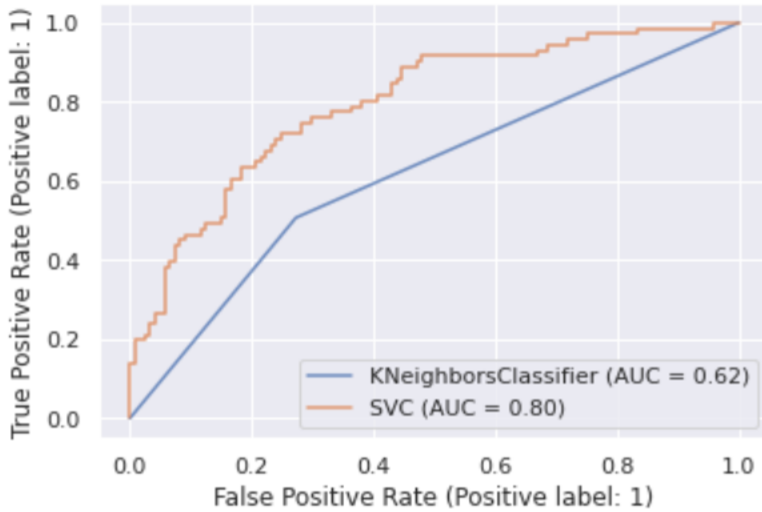

Figure 13: KNN ROC curve at KFold=2

LSTM model-Long Short Term Memory

After splitting data into training and testing set, the data range is normalized using MinMaxScaler library. To work with LSTM model the data is then split to inputs and outputs. We first split to input and output then reshape the data. Finally, after reshaping, the LSTM data model is applied to training data

```
------------------LSTM-------------------------
8
Model: "sequential_150"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_149 (Embedding)   (None, 8, 32)             160000

 lstm_149 (LSTM)             (None, 100)               53200

 dense_143 (Dense)           (None, 2)                 202

=================================================================
Total params: 213,402
Trainable params: 213,402
Non-trainable params: 0
_________________________________________________________________
```

Figure 14: LSTM model after input and output are well defined at KFold =2

```
lstm_model.fit(X_train, y_train, epochs=10, batch_size=1)
```

The line above is used so that the LSTM model can fit to the dataset. It returned an epoch of 10 layers. After training the model using fit() method. The accuracy scores were calculated using evaluate() method. Once the accuracy is calculated the prediction on lstm model is done on Label test data

```
scores = lstm_model.evaluate(Label_test, Label_test_tensor)
LSTM_accuracy = scores[1]*100
lstm_predicted = lstm_model.predict(Label_test)
```

However after this point there were some issues in running the confusion matrix on the ltsm model. So the result comparison table fills NaN values for the LTSM algorithm instead of the tp,fp,etc.. values that would have otherwise filled the table.

	tp	fp	fn	tn	fnrval	tprval	tnrval	fprval
Random Forest	114	15	24	39	0.380952	0.883721	0.619048	0.116279
KNN	100	29	23	40	0.365079	0.775194	0.634921	0.224806
LSTM	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Figure 15: At KFold=2, the comparison of tpr, tnr, fpr, fnr between 3 algorithms are shown.

The TP,TN, FP, FN values are retrieved using the confusion_matrix library. These values are used to calculate TPR, FPR, FNR, and TNR. Because confusion matrix was not run on LTSM algorithm, the table substitutes NaN values for LTSM row. Finally, Random Forest algorithm seemed to prove that it is most accurate model in predicting whether or not a person has diabetes. The benefit of training such a data on a classification model is, that in future if you provide certain attribute values corresponding to a single patient, then the model can output whether or not the patient has diabetes.

GitHub Link

https://github.com/ssm29njit/Mathew_Sheethal_634finalProject_Option1.git

References

1. Kaggle.com. 2021. *Pima Indians Diabetes Database*. [online] Available at: <https://www.kaggle.com/uciml/pima-indians-diabetes-database?select=diabetes.csv> [Accessed 5 December 2021].

2. Medium. 2021. *Evaluating a Random Forest model*. [online] Available at: <https://medium.com/analytics-vidhya/evaluating-a-random-forest-model-9d165595ad56> [Accessed 5 December 2021].

3. Kaggle.com. 2021. *Diabetes Classification-KNN-detailed*. [online] Available at: <https://www.kaggle.com/shrutimechlearn/step-by-step-diabetes-classification-knn-detailed/notebook> [Accessed 5 December 2021].

4. Scikit-learn.org. 2021. *ROC Curve with Visualization API*. [online] Available at: <https://scikit-learn.org/0.24/auto_examples/miscellaneous/plot_roc_curve_visualization_api.html> [Accessed 5 December 2021].

5. Colab.research.google.com. 2021. *Google Collaboratory*. [online] Available at: <https://colab.research.google.com/github/Gurubux/CognitiveClass-DL/blob/master/2_Deep_Learning_with_TensorFlow/DL_CC_2_3_RNN/3.4-Review-LSTM-MNIST-Database.ipynb> [Accessed 5 December 2021].

6. Kaggle.com. 2021. *LSTM & Machine Learning models*. [online] Available at: <https://www.kaggle.com/rahulvv/lstm-machine-learning-models-89-accuracy> [Accessed 5 December 2021].