

# BUILDING THE TRAINED MODEL

## DATA PREPROCESSING

```
In [1]: import pandas as pd
```

```
In [2]: dataset = pd.read_csv('../dataset/train_dataset.csv', index_col = 0)
```

```
In [3]: dataset.head()
```

```
Out[3]:
```

	trans_hour	trans_day	trans_month	trans_year	category	card_number	age	trans_amount	state	zip	fraud_risk
0	0	1	1	2019	12	6.300000e+11	54	66.21	22	49879	0
1	1	1	1	2019	3	3.540000e+15	15	55.81	14	62668	0
2	3	1	1	2019	8	5.020000e+11	60	8.68	4	96037	0
3	6	1	1	2019	4	3.530000e+15	44	89.52	40	29911	0
4	6	1	1	2019	0	2.350000e+15	72	1.90	38	16421	0

```
In [4]: import numpy as np
```

```
In [5]: x = dataset.iloc[ : , : 10].values  
y = dataset.iloc[ : , 10].values
```

```
In [6]: from sklearn.model_selection import train_test_split
```

```
In [7]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.15, random_state = 0)
```

```
In [8]: x_train.shape
```

Out[8]: (10210, 10)

```
In [9]: x_test.shape
```

Out[9]: (1802, 10)

```
In [10]: fraud = np.count_nonzero(y_train == 1)
         valid = np.count_nonzero(y_train == 0)
```

```
In [11]: print('Fraud cases in training data =', fraud)
         print('Valid cases in training data =', valid)
```

Fraud cases in training data = 5106  
Valid cases in training data = 5104

```
In [12]: from sklearn.preprocessing import StandardScaler
         scaler = StandardScaler()
```

```
In [13]: x_train = scaler.fit_transform(x_train)
         x_test = scaler.transform(x_test)
```

```
In [14]: x_train[ : 5]
```

```
Out[14]: array([[ 0.66337259,  1.24104545,  0.45653094, -0.37826057,  0.83408097,
                 -0.30554032,  2.3966382 , -0.73068363,  0.0181697 , -0.77660466],
                [-1.6023747 , -0.07304053, -0.90455674, -0.37826057, -1.22335066,
                 -0.30836573,  0.74498916, -0.74861649,  0.64443135,  0.93890762],
                [-1.12537527,  0.1459738 ,  0.45653094, -0.37826057,  0.57690202,
                 -0.30362247,  1.18542891, -0.79511806,  0.78360061, -1.2179066 ],
                [-1.6023747 , -0.29205486, -0.36012167, -0.37826057, -0.70899275,
                 -0.30397763,  1.46070375, -0.51118115, -1.58227676,  1.76478537],
                [-0.7676257 , -0.29205486, -1.44899181, -0.37826057, -0.70899275,
                 -0.30836532, -0.08083536,  0.02559291,  0.78360061, -1.18526965]])
```

```
In [15]: x_test[ : 5]
```

```
Out[15]: array([[ 1.02112216, -0.51106919,  1.27318354, -0.37826057,  1.34843888,
                  3.15638262,  0.35960438,  1.60624238,  0.64443135,  0.91726066],
```

```
[-0.05212655, 0.58400246, 0.1843134, -0.37826057, 0.83408097,  
-0.30822372, -0.08083536, -0.65192446, 0.29650821, -1.52769864],  
[ 1.14037202, 1.56956694, 0.72874847, -0.37826057, 1.09125992,  
-0.30560345, 1.29553884, 1.71351642, 1.13152375, 1.07356281],  
[ 1.02112216, -0.73008352, 0.1843134, -0.37826057, 1.09125992,  
-0.30500363, 1.51575871, 1.6205402, 0.15733896, 0.77172649],  
[-1.6023747, -0.07304053, -0.08790413, -0.37826057, 1.34843888,  
-0.30819767, 0.80004413, -0.06571388, -0.60809196, 0.84854544]])
```

## LOGISTIC REGRESSION (LR)

```
In [16]: from sklearn.linear_model import LogisticRegression  
LR_model = LogisticRegression(random_state = 0)  
LR_model.fit(x_train, y_train)
```

```
Out[16]: LogisticRegression(random_state=0)
```

```
In [17]: y_pred = LR_model.predict(x_test)
```

```
In [18]: from sklearn.metrics import accuracy_score
```

```
In [19]: acc_lr = accuracy_score(y_test, y_pred)
```

```
In [20]: print(acc_lr)
```

```
0.8485016648168702
```

## K-NEAREST NEIGHBORS (KNN)

```
In [21]: from sklearn.neighbors import KNeighborsClassifier  
KNN_model = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)  
KNN_model.fit(x_train, y_train)
```

```
Out[21]: KNeighborsClassifier()
```

```
In [22]: y_pred = KNN_model.predict(x_test)
```

```
In [23]: acc_knn = accuracy_score(y_test, y_pred)
```

```
In [24]: print(acc_knn)
```

0.8657047724750278

SUPPORT VECTOR MACHINE (SVM)

```
In [25]: from sklearn.svm import SVC
SVM_model = SVC(kernel = 'linear', random_state = 0)
SVM_model.fit(x_train, y_train)
```

```
Out[25]: SVC(kernel='linear', random_state=0)
```

```
In [26]: y_pred = SVM_model.predict(x_test)
```

```
In [27]: acc_svm = accuracy_score(y_test, y_pred)
```

```
In [28]: print(acc_svm)
```

0.8479467258601554

NAIVE BAYES (NB)

```
In [29]: from sklearn.naive_bayes import GaussianNB
NB_model = GaussianNB()
NB_model.fit(x_train, y_train)
```

```
Out[29]: GaussianNB()
```

```
In [30]: y_pred = NB_model.predict(x_test)
```

```
In [31]: acc_nb = accuracy_score(y_test, y_pred)
```

```
In [32]: print(acc_nb)
```

0.8496115427302997

DECISION TREE (DT)

```
In [33]: from sklearn.tree import DecisionTreeClassifier
DT_model = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
DT_model.fit(x_train, y_train)
```

Out[33]: DecisionTreeClassifier(criterion='entropy', random\_state=0)

```
In [34]: y_pred = DT_model.predict(x_test)
```

```
In [35]: acc_dt = accuracy_score(y_test, y_pred)
```

```
In [36]: print(acc_dt)
```

0.967258601553829

RANDOM FOREST (RF)

```
In [37]: from sklearn.ensemble import RandomForestClassifier
RF_model = RandomForestClassifier()
RF_model.fit(x_train, y_train)
```

Out[37]: RandomForestClassifier()

```
In [38]: y_pred = RF_model.predict(x_test)
```

```
In [39]: acc_rf = accuracy_score(y_test, y_pred)
```

```
In [40]: print(acc_rf)
```

0.9705882352941176

ARTIFICIAL NEURAL NETWORK (ANN)

```
In [41]: import tensorflow as tf
```

```
In [42]: ANN_model = tf.keras.models.Sequential()
```

```
In [43]: ANN_model.add(tf.keras.layers.Dense(64, input_dim = 10, activation = 'relu'))
ANN_model.add(tf.keras.layers.Dense(128, activation = 'relu'))
ANN_model.add(tf.keras.layers.Dense(1, activation = 'sigmoid'))
```

```
In [44]: ANN_model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

```
In [45]: ANN_model.fit(x_train, y_train, batch_size = 32, epochs = 200)
```

```
Epoch 1/200
320/320 [=====] - 1s 1ms/step - loss: 0.4871 - accuracy: 0.7848
Epoch 2/200
320/320 [=====] - 0s 1ms/step - loss: 0.3288 - accuracy: 0.8532
Epoch 3/200
320/320 [=====] - 0s 1ms/step - loss: 0.3058 - accuracy: 0.8604
Epoch 4/200
320/320 [=====] - 0s 1ms/step - loss: 0.3019 - accuracy: 0.8578
Epoch 5/200
320/320 [=====] - 0s 1ms/step - loss: 0.2956 - accuracy: 0.8622
Epoch 6/200
320/320 [=====] - 0s 1ms/step - loss: 0.2859 - accuracy: 0.8675
Epoch 7/200
320/320 [=====] - 0s 1ms/step - loss: 0.2853 - accuracy: 0.8706
Epoch 8/200
320/320 [=====] - 0s 1ms/step - loss: 0.2643 - accuracy: 0.8806
Epoch 9/200
320/320 [=====] - 0s 1ms/step - loss: 0.2739 - accuracy: 0.8755
Epoch 10/200
320/320 [=====] - 0s 1ms/step - loss: 0.2706 - accuracy: 0.8765
Epoch 11/200
320/320 [=====] - 0s 1ms/step - loss: 0.2590 - accuracy: 0.8826
Epoch 12/200
320/320 [=====] - 0s 1ms/step - loss: 0.2601 - accuracy: 0.8851
Epoch 13/200
320/320 [=====] - 0s 1ms/step - loss: 0.2406 - accuracy: 0.8971
Epoch 14/200
320/320 [=====] - 0s 1ms/step - loss: 0.2290 - accuracy: 0.9060
Epoch 15/200
320/320 [=====] - 0s 1ms/step - loss: 0.2254 - accuracy: 0.9096
```

Epoch 16/200  
320/320 [=====] - ETA: 0s - loss: 0.2096 - accuracy: 0.91 - 0s 1ms/step - loss: 0.2097 - accuracy: 0.9156  
Epoch 17/200  
320/320 [=====] - 0s 1ms/step - loss: 0.2094 - accuracy: 0.9132  
Epoch 18/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1947 - accuracy: 0.9230  
Epoch 19/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1955 - accuracy: 0.9206  
Epoch 20/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1868 - accuracy: 0.9309  
Epoch 21/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1732 - accuracy: 0.9318  
Epoch 22/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1698 - accuracy: 0.9302  
Epoch 23/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1753 - accuracy: 0.9272  
Epoch 24/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1633 - accuracy: 0.9363  
Epoch 25/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1552 - accuracy: 0.9382  
Epoch 26/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1541 - accuracy: 0.9405  
Epoch 27/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1529 - accuracy: 0.9411  
Epoch 28/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1526 - accuracy: 0.9409  
Epoch 29/200  
320/320 [=====] - 0s 985us/step - loss: 0.1434 - accuracy: 0.9438  
Epoch 30/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1384 - accuracy: 0.9466  
Epoch 31/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1319 - accuracy: 0.9481  
Epoch 32/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1401 - accuracy: 0.9447  
Epoch 33/200  
320/320 [=====] - 0s 995us/step - loss: 0.1318 - accuracy: 0.9484  
Epoch 34/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1246 - accuracy: 0.9519  
Epoch 35/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1233 - accuracy: 0.9534  
Epoch 36/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1247 - accuracy: 0.9502  
Epoch 37/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1296 - accuracy: 0.9467  
Epoch 38/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1399 - accuracy: 0.9414  
Epoch 39/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1210 - accuracy: 0.9517

Epoch 40/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1194 - accuracy: 0.9515  
Epoch 41/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1158 - accuracy: 0.9559  
Epoch 42/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1188 - accuracy: 0.9526  
Epoch 43/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1130 - accuracy: 0.9553  
Epoch 44/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1144 - accuracy: 0.9560  
Epoch 45/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1209 - accuracy: 0.9546  
Epoch 46/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1094 - accuracy: 0.9572  
Epoch 47/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1043 - accuracy: 0.9597  
Epoch 48/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1227 - accuracy: 0.9505  
Epoch 49/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1125 - accuracy: 0.9558  
Epoch 50/200  
320/320 [=====] - 0s 994us/step - loss: 0.1084 - accuracy: 0.9581  
Epoch 51/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1106 - accuracy: 0.9566  
Epoch 52/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1159 - accuracy: 0.9539  
Epoch 53/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1127 - accuracy: 0.9567  
Epoch 54/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1082 - accuracy: 0.9578  
Epoch 55/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1022 - accuracy: 0.9629  
Epoch 56/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1071 - accuracy: 0.9571  
Epoch 57/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0956 - accuracy: 0.9642  
Epoch 58/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1034 - accuracy: 0.9611  
Epoch 59/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1070 - accuracy: 0.9563  
Epoch 60/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0926 - accuracy: 0.9660  
Epoch 61/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0983 - accuracy: 0.9607  
Epoch 62/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0972 - accuracy: 0.9667  
Epoch 63/200  
320/320 [=====] - 0s 1ms/step - loss: 0.1016 - accuracy: 0.9611  
Epoch 64/200



320/320 [=====] - 0s 1ms/step - loss: 0.0973 - accuracy: 0.9616  
Epoch 65/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0939 - accuracy: 0.9635  
Epoch 66/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0961 - accuracy: 0.9665  
Epoch 67/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0933 - accuracy: 0.9638  
Epoch 68/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0921 - accuracy: 0.9629  
Epoch 69/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0845 - accuracy: 0.9661  
Epoch 70/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0984 - accuracy: 0.9603  
Epoch 71/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0890 - accuracy: 0.9657  
Epoch 72/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0912 - accuracy: 0.9630  
Epoch 73/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0861 - accuracy: 0.9675  
Epoch 74/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0808 - accuracy: 0.9696  
Epoch 75/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0829 - accuracy: 0.9693  
Epoch 76/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0836 - accuracy: 0.9662  
Epoch 77/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0824 - accuracy: 0.9666  
Epoch 78/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0795 - accuracy: 0.9657  
Epoch 79/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0824 - accuracy: 0.9685  
Epoch 80/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0773 - accuracy: 0.9698  
Epoch 81/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0744 - accuracy: 0.9726  
Epoch 82/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0757 - accuracy: 0.9732  
Epoch 83/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0779 - accuracy: 0.9677  
Epoch 84/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0790 - accuracy: 0.9659  
Epoch 85/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0828 - accuracy: 0.9653  
Epoch 86/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0807 - accuracy: 0.9665  
Epoch 87/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0759 - accuracy: 0.9681  
Epoch 88/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0761 - accuracy: 0.9709

Epoch 89/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0809 - accuracy: 0.9682  
Epoch 90/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0744 - accuracy: 0.9723  
Epoch 91/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0739 - accuracy: 0.9720  
Epoch 92/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0714 - accuracy: 0.9738  
Epoch 93/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0713 - accuracy: 0.9732  
Epoch 94/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0964 - accuracy: 0.9623  
Epoch 95/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0727 - accuracy: 0.9721  
Epoch 96/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0678 - accuracy: 0.9731  
Epoch 97/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0976 - accuracy: 0.9663  
Epoch 98/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0671 - accuracy: 0.9730  
Epoch 99/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0750 - accuracy: 0.9694  
Epoch 100/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0634 - accuracy: 0.9781  
Epoch 101/200  
320/320 [=====] - 0s 992us/step - loss: 0.0732 - accuracy: 0.9715  
Epoch 102/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0698 - accuracy: 0.9735  
Epoch 103/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0626 - accuracy: 0.9782  
Epoch 104/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0632 - accuracy: 0.9777  
Epoch 105/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0630 - accuracy: 0.9768  
Epoch 106/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0652 - accuracy: 0.9735  
Epoch 107/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0617 - accuracy: 0.9775  
Epoch 108/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0788 - accuracy: 0.9686  
Epoch 109/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0619 - accuracy: 0.9770  
Epoch 110/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0647 - accuracy: 0.9745  
Epoch 111/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0601 - accuracy: 0.9784  
Epoch 112/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0608 - accuracy: 0.9791  
Epoch 113/200

320/320 [=====] - 0s 1ms/step - loss: 0.0604 - accuracy: 0.9758  
Epoch 114/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0592 - accuracy: 0.9784  
Epoch 115/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0625 - accuracy: 0.9750  
Epoch 116/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0568 - accuracy: 0.9752  
Epoch 117/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0587 - accuracy: 0.9789  
Epoch 118/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0607 - accuracy: 0.9759  
Epoch 119/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0599 - accuracy: 0.9776  
Epoch 120/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0689 - accuracy: 0.9761  
Epoch 121/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0557 - accuracy: 0.9799  
Epoch 122/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0573 - accuracy: 0.9786  
Epoch 123/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0588 - accuracy: 0.9779  
Epoch 124/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0577 - accuracy: 0.9785  
Epoch 125/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0690 - accuracy: 0.9728  
Epoch 126/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0522 - accuracy: 0.9803  
Epoch 127/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0624 - accuracy: 0.9742  
Epoch 128/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0519 - accuracy: 0.9783  
Epoch 129/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0503 - accuracy: 0.9826  
Epoch 130/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0450 - accuracy: 0.9845  
Epoch 131/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0648 - accuracy: 0.9751  
Epoch 132/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0509 - accuracy: 0.9800  
Epoch 133/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0480 - accuracy: 0.9816  
Epoch 134/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0481 - accuracy: 0.9823  
Epoch 135/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0543 - accuracy: 0.9772  
Epoch 136/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0500 - accuracy: 0.9821  
Epoch 137/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0437 - accuracy: 0.9834

Epoch 138/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0465 - accuracy: 0.9828  
Epoch 139/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0465 - accuracy: 0.9819  
Epoch 140/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0502 - accuracy: 0.9818  
Epoch 141/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0509 - accuracy: 0.9776  
Epoch 142/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0520 - accuracy: 0.9785  
Epoch 143/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0475 - accuracy: 0.9812  
Epoch 144/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0485 - accuracy: 0.9824  
Epoch 145/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0442 - accuracy: 0.9837  
Epoch 146/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0440 - accuracy: 0.9844  
Epoch 147/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0447 - accuracy: 0.9845  
Epoch 148/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0385 - accuracy: 0.9850  
Epoch 149/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0393 - accuracy: 0.9848  
Epoch 150/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0544 - accuracy: 0.9774  
Epoch 151/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0398 - accuracy: 0.9855  
Epoch 152/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0396 - accuracy: 0.9846  
Epoch 153/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0429 - accuracy: 0.9813  
Epoch 154/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0417 - accuracy: 0.9824  
Epoch 155/200  
320/320 [=====] - ETA: 0s - loss: 0.0404 - accuracy: 0.98 - 0s 1ms/step - loss: 0.0405 - accuracy: 0.9851  
Epoch 156/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0394 - accuracy: 0.9848  
Epoch 157/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0431 - accuracy: 0.9836  
Epoch 158/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0392 - accuracy: 0.9857: 0s - loss: 0.0363 - accuracy: 0.9872  
Epoch 159/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0391 - accuracy: 0.9872  
Epoch 160/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0381 - accuracy: 0.9882  
Epoch 161/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0367 - accuracy: 0.9873

Epoch 162/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0392 - accuracy: 0.9835  
Epoch 163/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0478 - accuracy: 0.9819  
Epoch 164/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0346 - accuracy: 0.9875  
Epoch 165/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0349 - accuracy: 0.9865  
Epoch 166/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0346 - accuracy: 0.9890  
Epoch 167/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0408 - accuracy: 0.9841  
Epoch 168/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0290 - accuracy: 0.9903  
Epoch 169/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0346 - accuracy: 0.9873  
Epoch 170/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0378 - accuracy: 0.9871  
Epoch 171/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0382 - accuracy: 0.9867  
Epoch 172/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0429 - accuracy: 0.9852  
Epoch 173/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0303 - accuracy: 0.9904  
Epoch 174/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0322 - accuracy: 0.9878  
Epoch 175/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0305 - accuracy: 0.9893  
Epoch 176/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0295 - accuracy: 0.9893  
Epoch 177/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0366 - accuracy: 0.9867  
Epoch 178/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0379 - accuracy: 0.9865  
Epoch 179/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0293 - accuracy: 0.9888  
Epoch 180/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0373 - accuracy: 0.9874  
Epoch 181/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0286 - accuracy: 0.9911  
Epoch 182/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0352 - accuracy: 0.9881  
Epoch 183/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0297 - accuracy: 0.9893  
Epoch 184/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0302 - accuracy: 0.9894  
Epoch 185/200  
320/320 [=====] - 0s 1ms/step - loss: 0.0275 - accuracy: 0.9909  
Epoch 186/200

```

320/320 [=====] - 0s 1ms/step - loss: 0.0309 - accuracy: 0.9889
Epoch 187/200
320/320 [=====] - 0s 1ms/step - loss: 0.0401 - accuracy: 0.9861
Epoch 188/200
320/320 [=====] - 0s 1ms/step - loss: 0.0273 - accuracy: 0.9900
Epoch 189/200
320/320 [=====] - 0s 1ms/step - loss: 0.0292 - accuracy: 0.9918
Epoch 190/200
320/320 [=====] - 0s 1ms/step - loss: 0.0449 - accuracy: 0.9816
Epoch 191/200
320/320 [=====] - 0s 1ms/step - loss: 0.0249 - accuracy: 0.9933
Epoch 192/200
320/320 [=====] - 0s 1ms/step - loss: 0.0262 - accuracy: 0.9917
Epoch 193/200
320/320 [=====] - 0s 1ms/step - loss: 0.0225 - accuracy: 0.9938
Epoch 194/200
320/320 [=====] - 0s 1ms/step - loss: 0.0275 - accuracy: 0.9899
Epoch 195/200
320/320 [=====] - 0s 1ms/step - loss: 0.0263 - accuracy: 0.9917
Epoch 196/200
320/320 [=====] - 0s 1ms/step - loss: 0.0305 - accuracy: 0.9889
Epoch 197/200
320/320 [=====] - 0s 1ms/step - loss: 0.0465 - accuracy: 0.9824
Epoch 198/200
320/320 [=====] - 0s 1ms/step - loss: 0.0218 - accuracy: 0.9938
Epoch 199/200
320/320 [=====] - 0s 1ms/step - loss: 0.0225 - accuracy: 0.9925
Epoch 200/200
320/320 [=====] - 0s 1ms/step - loss: 0.0243 - accuracy: 0.9932

```

Out[45]: <tensorflow.python.keras.callbacks.History at 0x1c56862beb0>

```
In [46]: loss, acc_ann = ANN_model.evaluate(x_train, y_train, verbose = 0)
```

```
In [47]: print(acc_ann)
```

0.994025468826294

```
In [48]: y_pred = ANN_model.predict(x_test)
y_pred[y_pred <= 0.5] = 0
y_pred[y_pred > 0.5] = 1
```

ACCURACY COMPARISON OF ALL THE MODELS

In [49]:

```
scores = [acc_lr * 100,  
          acc_knn * 100,  
          acc_svm * 100,  
          acc_nb * 100,  
          acc_dt * 100,  
          acc_rf * 100,  
          acc_ann * 100]
```

```
In [50]: names = ["Logistic Regression",  
                  "K-Nearest Neighbors",  
                  "Support Vector Machine",  
                  "Naive Bayes",  
                  "Decision Tree",  
                  "Random Forest",  
                  "Artificial Neural Network"]
```

```
In [51]: df = pd.DataFrame()  
df['Algorithm Name'] = names  
df['Accuracy Score (%)'] = scores  
df = df.sort_values('Accuracy Score (%)', ascending = False)
```

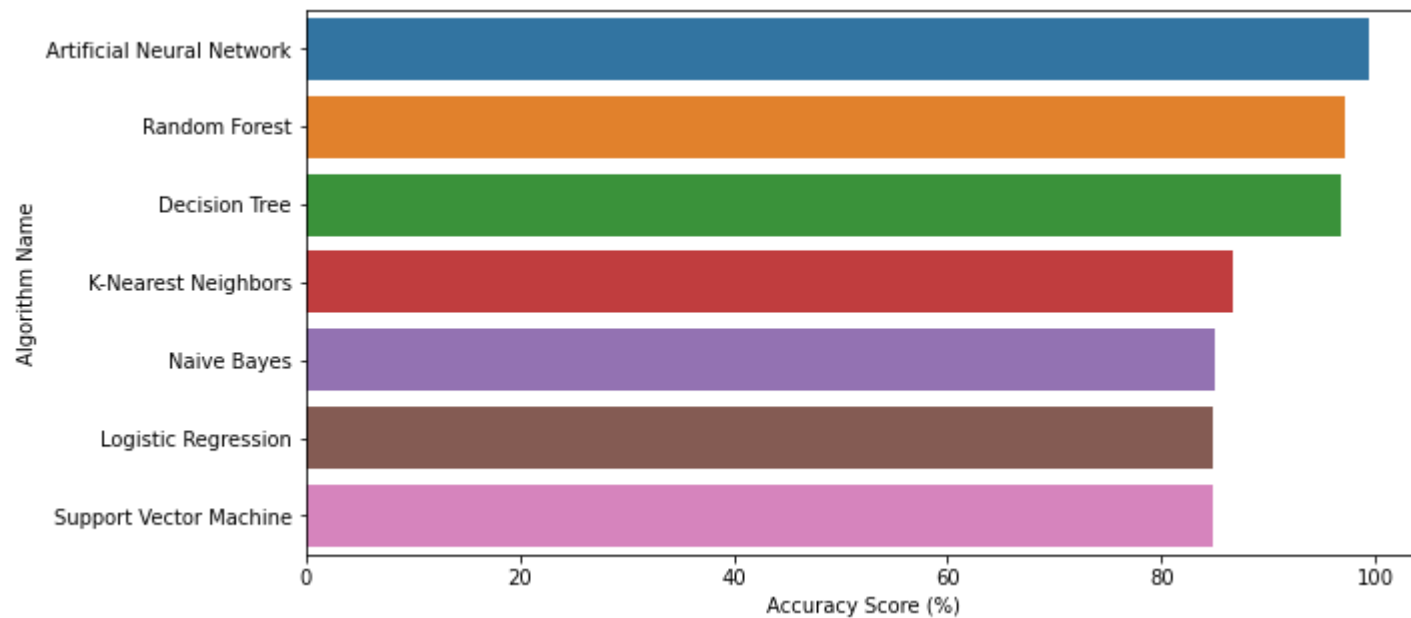
```
In [52]: df
```

```
Out[52]:
```

	Algorithm Name	Accuracy Score (%)
6	Artificial Neural Network	99.402547
5	Random Forest	97.058824
4	Decision Tree	96.725860
1	K-Nearest Neighbors	86.570477
3	Naive Bayes	84.961154
0	Logistic Regression	84.850166
2	Support Vector Machine	84.794673

```
In [53]: import matplotlib.pyplot as plt  
import seaborn as sns
```

```
In [54]: fig = plt.subplots(figsize = (10, 5))  
ax = sns.barplot(x = "Accuracy Score (%)", y = "Algorithm Name", data = df)
```



#### SAVING THE BEST TRAINED MODEL

```
In [55]: import os.path
```

```
In [56]: if os.path.isfile('../model/project_model.h5') is False:  
ANN_model.save('../model/project_model.h5')
```

```
In [ ]:
```