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In [1]: # Team Members

# Poja Goyal
# Roshan Sah
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# Sushant Yadav
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In [2]: # Importing Libraries

import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image
import numpy as np
from imblearn.over_sampling import SMOTE

import tensorflow as tf
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Conv2D, Flatten, MaxPool2D

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import *
from sklearn.linear_model import LogisticRegression

import reoborn as sns
import joblib

from sklearn.tree import export_graphviz
import six
import pydot
from sklearn import tree
```

```
In [3]: # Load data
data = pd.DataFrame(pd.read_csv('datasets/mcl.csv'))
print(data.shape)
```

```
In [4]: (data.head())
```

	ID	LOC_BLKANK	BRANCH_COUNT	CALL_PAIRS	LOC_CODE_AND_COMMENT	LOC_COMMENTS	CONDITION_COUNT	CYCLOMATIC_COMPLEXITY
0	1	0	1	0	0	0	0	
1	2	0	1	0	0	0	0	
2	3	0	1	1	0	0	0	
3	4	8	7	11	32	3	12	
4	5	4	17	1	1	8	12	

5 rows × 9 columns

```
In [5]: # Check if any value is null
isAnyValueNull = data.isnull().values.any()
print('Is Any Value Null?', isAnyValueNull)
```

Is Any Value Null: False

```
In [6]: # Pre-processing Data
if isAnyValueNull:
    data = data.dropna()
data_X = data.drop(['defects'], axis=1)
y_train, X_test, y_train, y_test = train_test_split(data_X, data_y, test_size = 0.1, random_state=1)
X_train, X_val, y_train, y_val = sm.fit_sample(X_train, y_train)

X_train, X_val, y_train, y_val = train_test_split(X_train2, y_train2, test_size = .1, random_state=1)
combined_training_data = X_train.copy()
combined_training_data['defects'] = y_train
```

```
In [7]: all_data = [data, data_X, data_y, combined_training_data, X_train1, X_train2, X_train, X_test, X_val, y_train]
y_model = model.fit(X_train, y_train, batch_size = 16, epochs = 100, validation_data=(X_val, y_val))
corr = combined_training_data.corr()
sns.heatmap(corr, linewidth=0.1, vmin=0.5, vmax=1)
```



```
In [8]: def plot_loss_accuracy_graph(history):
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()

# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```

```
In [9]: # Predict Test Data
def predict_test_data(model, X_val=X_val):
# Predict the output of test data from trained model
y_pred = model.predict(X_val)
y_pred = (y_pred > 0.5)
y_pred = pd.DataFrame(y_pred, columns=['defects'])

# Confusion Matrix
cm = confusion_matrix(y_val, y_pred)

# Calculate the accuracy between actual output and predicted output
return accuracy_score(y_val, y_pred)
```

```
In [10]: # Model train
def neural_network():
model = Sequential()
# First hidden layer
model.add(Dense(units = 16, activation = 'relu', input_dim = len(data_X.columns)))
# Second hidden layer
model.add(Dense(units = 8, activation = 'relu'))
# Third hidden layer
model.add(Dense(units = 4, activation = 'relu'))
# Output layer
model.add(Dense(units = 1, activation = 'sigmoid'))

# Compiling Artificial Neural Network
model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])

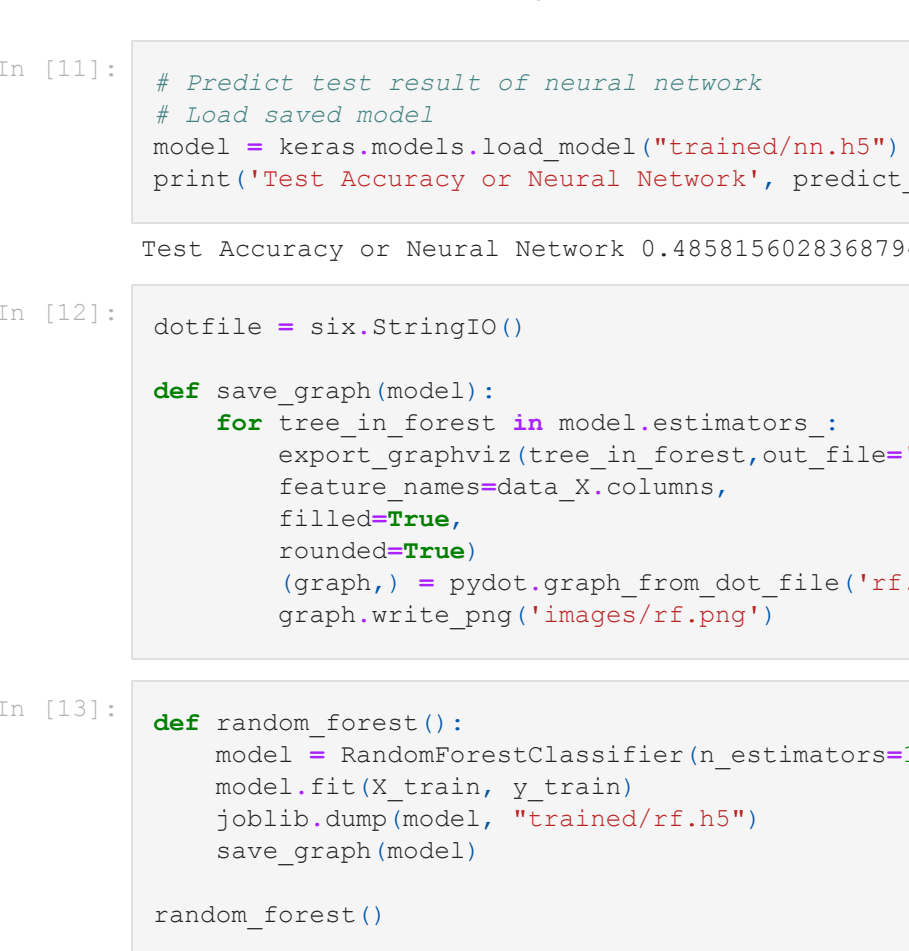
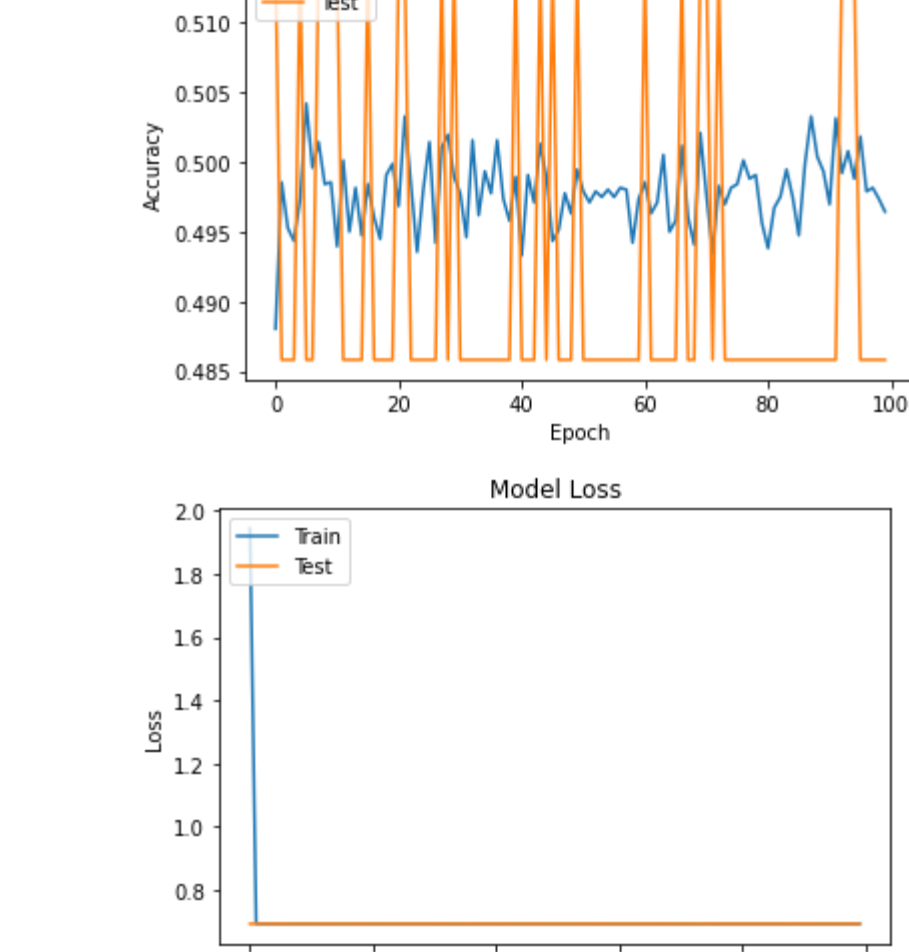
# Fitting the ANN to the Training set
history = model.fit(X_train, y_train, batch_size = 16, epochs = 100, validation_data=(X_val, y_val))

model.save('trained/nn.h5',
overwrite=True,
include_optimizer=True,
save_format=None,
signature=None,
options=None,
save_traces=True,
)

plot_loss_accuracy_graph(history)

neural_network()

Epoch 1/100
552/552 [=====] - 1s 1ms/step - loss: 1.9439 - accuracy: 0.4880 - val_loss: 0.6930 - v
al_accuracy: 0.5142
Epoch 2/100
552/552 [=====] - 1s 83us/step - loss: 0.6932 - accuracy: 0.4986 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 3/100
552/552 [=====] - 1s 87us/step - loss: 0.6932 - accuracy: 0.4953 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 4/100
552/552 [=====] - 1s 873us/step - loss: 0.6932 - accuracy: 0.4944 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 5/100
552/552 [=====] - 1s 863us/step - loss: 0.6931 - accuracy: 0.5042 - val_loss: 0.6935 -
val_accuracy: 0.4858
Epoch 6/100
552/552 [=====] - 1s 1ms/step - loss: 0.6932 - accuracy: 0.4996 - val_loss: 0.6934 - v
al_accuracy: 0.4858
Epoch 7/100
552/552 [=====] - 1s 926us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6931 -
val_accuracy: 0.5142
Epoch 8/100
552/552 [=====] - 1s 874us/step - loss: 0.6932 - accuracy: 0.4984 - val_loss: 0.6931 -
val_accuracy: 0.5142
Epoch 9/100
552/552 [=====] - 1s 877us/step - loss: 0.6932 - accuracy: 0.4986 - val_loss: 0.6931 -
val_accuracy: 0.5142
Epoch 10/100
552/552 [=====] - 1s 854us/step - loss: 0.6932 - accuracy: 0.4940 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 11/100
552/552 [=====] - 1s 881us/step - loss: 0.6932 - accuracy: 0.5001 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 12/100
552/552 [=====] - 1s 880us/step - loss: 0.6932 - accuracy: 0.4950 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 13/100
552/552 [=====] - 1s 865us/step - loss: 0.6932 - accuracy: 0.4982 - val_loss: 0.6934 -
val_accuracy: 0.4858
Epoch 14/100
552/552 [=====] - 1s 863us/step - loss: 0.6932 - accuracy: 0.4947 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 15/100
552/552 [=====] - 1s 856us/step - loss: 0.6932 - accuracy: 0.4984 - val_loss: 0.6931 -
val_accuracy: 0.5142
Epoch 16/100
552/552 [=====] - 1s 909us/step - loss: 0.6932 - accuracy: 0.4961 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 17/100
552/552 [=====] - 1s 895us/step - loss: 0.6932 - accuracy: 0.4945 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 18/100
552/552 [=====] - 1s 888us/step - loss: 0.6932 - accuracy: 0.4991 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 19/100
552/552 [=====] - 1s 885us/step - loss: 0.6932 - accuracy: 0.4999 - val_loss: 0.6932 -
val_accuracy: 0.5142
Epoch 20/100
552/552 [=====] - 1s 876us/step - loss: 0.6932 - accuracy: 0.4968 - val_loss: 0.6931 -
val_accuracy: 0.5142
Epoch 21/100
552/552 [=====] - 1s 868us/step - loss: 0.6932 - accuracy: 0.5033 - val_loss: 0.6930 -
val_accuracy: 0.4858
Epoch 22/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 23/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 24/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 25/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 26/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 27/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 28/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 29/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 30/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 31/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 32/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 33/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 34/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 35/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 36/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 37/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 38/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 39/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 40/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 41/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 42/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 43/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 44/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 45/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 46/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 47/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 48/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 49/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 50/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 51/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 52/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 53/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 54/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 55/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 56/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 57/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 58/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 59/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 60/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 61/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 62/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 63/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 64/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 65/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 66/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 67/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 68/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 69/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 70/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 71/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 72/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 73/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 74/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 75/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 76/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 77/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 78/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 79/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 80/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 81/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 82/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 83/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 84/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 85/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 86/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 87/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 88/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 89/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 90/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 91/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 92/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 93/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.4978 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 94/100
552/552 [=====] - 1s 872us/step - loss: 0.6932 - accuracy: 0.4936 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 95/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4980 - val_loss: 0.6932 -
val_accuracy: 0.4858
Epoch 96/100
552/552 [=====] - 1s 886us/step - loss: 0.6932 - accuracy: 0.5014 - val_loss: 0.6933 -
val_accuracy: 0.4858
Epoch 97/100
552/552 [=====] - 1s 866us/step - loss: 0.6932 - accuracy: 0.4942 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 98/100
552/552 [=====] - 1s 870us/step - loss: 0.6932 - accuracy: 0.5011 - val_loss: 0.6931 -
val_accuracy: 0.4858
Epoch 99/100
552/552 [=====] - 1s 893us/step - loss: 0.6932 - accuracy: 0.5020 - val_loss: 0.6933 -
val_accuracy: 0.5142
Epoch 100/100
552/552 [=====] - 1s 883us/step - loss: 0.6932 - accuracy: 0.4989 - val_loss: 0.6931 -
val_accuracy: 0.4858
```



```
In [11]: # Predict Test result of neural network
# Load saved model
model = keras.models.load_model('trained/nn.h5')
print('Test Accuracy of Neural Network', predict_test_data(model))
```

Test Accuracy of Neural Network 0.4858156028368794

```
In [12]: dotfile = six.StringIO()

def save_graph(model):
    tree = tree.export_graphviz(model.estimators_[0],
                                out_file='rf.dot',
                                feature_names=data_X.columns,
                                filled=True,
                                rounded=True,
                                node_ids=True)
    (graph,) = pydot.graph_from_dot_file('rf.dot')
    graph.write_png('images/rf.png')
```

```
In [13]: # Random Forest
def random_forest():
model = RandomForestClassifier(n_estimators=10, max_depth=5, random_state=0)
model.fit(X_train, y_train)
joblib.dump(model, "trained/rf.h5")
save_graph(model)
random_forest()
```

```
In [14]: img = image.imread('images/rf.png')
plt.figure(figsize=(20, 20))
plt.imshow(img)
plt.show()
```



```
In [15]: # Predict Test result of random forest
model = joblib.load('trained/rf.h5')
print('Test Accuracy of Random Forest', predict_test_data(model))
```

Test Accuracy of Random Forest 0.963356739932719

```
In [16]: def svm():
model = SVC(gamma='auto')
model.fit(X_train, y_train)
joblib.dump(model, "trained/svm.h5")
svm()
```

```
In [17]: # Predict Test result of svm
model = joblib.load('trained/svm.h5')
print('Test Accuracy of SVC', predict_test_data(model))
```

Test Accuracy of SVC 0.7446808510638298

```
In [18]: def cnn():
global X_val1
X_train_matrix = X_train.values
X_val_matrix = X_val.values
y_train_matrix = y_train.values
y_val_matrix = y_val.values

y_train_series = y_train
y_val_series = y_val

img_rows, img_cols = 1, len(data_X.columns)

X_train1 = X_train_matrix.reshape(X_train_matrix.shape[0], img_rows, img_cols, 1)
X_val1 = X_val_matrix.reshape(X_val_matrix.shape[0], img_rows, img_cols, 1)
input_shape = (img_rows, img_cols, 1)

model = Sequential()
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu', input_shape=input_shape))
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(16, kernel_size=(3, 3), activation='relu'))
model.add(Flatten())
model.add(Dense(8, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

# Compile model using accuracy to measure model performance
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

#train the model
history = model.fit(X_train1, y_train_matrix, batch_size=16, epochs=100, validation_data=(X_val1, y_val_ma

model.save('trained/cnn.h5',
overwrite=True,
include_optimizer=True,
save_format=None,
signature=None,
options=None,
save_traces=True,
)

plot_loss_accuracy_graph(history)

cnn()
```