

## Appendix A. Algorithms and Coding

### A.1. Common Preconditions for Construction of Models

#### A.1.1. Importing Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import Dropout
from keras.layers import Conv1D, MaxPooling1D
from numpy import ndarray
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from tensorflow import keras
from keras.layers.core import Activation, Dense
from keras.preprocessing import sequence
from sklearn.model_selection import train_test_split
from keras.models import load_model
from tensorflow.keras.callbacks import TensorBoard
```

#### A.1.2. Importing Modeling Data of this Study and Confirming the Number of Samples and Variables

```
df = pd.read_excel ("BD.xlsx")
df.shape
```

#### A.1.3. Data Pre-Processing

##### Dividing Data into Training Dataset, Test Dataset, and Validation Dataset

```
df_num = df.shape (0)
indexes = np.random.permutation (df_num)
train_indexes = indexes (:int (df_num *0.7))
test_indexes = indexes (int(df_num *0.7):)
train_df = df.loc (train_indexes)
test_df= df.loc(test_indexes)
```

##### Normalize Data by Converting their Values to 0 to 1

```
scaler = MinMaxScaler (feature_range= (0,1))
df= scaler.fit_transform (df)
```

##### Defining dependent and independent variables

```
x_train = np.array (train_df.drop ('FC', axis = 'columns'))
y_train = np.array (train_df('FC'))
x_test = np.array (test_df.drop ('FC', axis = 'columns'))
y_test = np.array (test_df ('FC'))
```

##### Transforming Data Dimensions to Conform to the Model Input Conditions

```
x_train = np.reshape (x_train, (x_train.shape (0), 1, x_train.shape (1)))
x_test = np.reshape (x_test, (x_test.shape (0), 1, x_test.shape (1)))
```

## A.2. Modeling–Inputting when Individual Models are Constructed

### A.2.1. Deep Neural Networks

```

model = Sequential ()
model.add (Flatten(input_shape = (x_train.shape (1),
x_train.shape (2))))
model.add (Dense (16, activation = 'relu'))
model.add (Dropout(0.25))
model.add (Dense(16, activation = 'relu'))
model.add (Dropout (0.25))
model.add (Dense (8, activation = 'relu'))
model.add (Dropout (0.25))
model.add (Dense(1, activation = 'sigmoid'))
model.compile (loss = "binary_crossentropy", optimizer =
"adam",metrics = ('accuracy'))
model.summary ()

```

### A.2.2. Deep Neural Networks without Selecting Variables

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 23)	0
dense (Dense)	(None, 32)	768
dropout (Dropout)	(None, 32)	0
dense_1 (Dense)	(None, 8)	264
dropout_1 (Dropout)	(None, 8)	0
dense_2 (Dense)	(None, 8)	72
dropout_2 (Dropout)	(None, 8)	0
dense_3 (Dense)	(None, 1)	9
Total params: 1,113		
Trainable params: 1,113		
Non-trainable params: 0		

### A.2.3. Deep Neural Networks after Selection by CHAID

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 9)	0
dense (Dense)	(None, 16)	160
dropout (Dropout)	(None, 16)	0
dense_1 (Dense)	(None, 16)	272
dropout_1 (Dropout)	(None, 16)	0
dense_2 (Dense)	(None, 8)	136
dropout_2 (Dropout)	(None, 8)	0
dense_3 (Dense)	(None, 1)	9
Total params: 577		
Trainable params: 577		
Non-trainable params: 0		

#### A.2.4. Convolutional Neural Networks

```
model = Sequential ()
model.add (Conv1D (filters = 16,
kernel_size = (1),
padding = 'same',
input_shape = (x_train.shape (1), x_train.shape (2)),
activation = 'relu'))
model.add (MaxPooling1D (pool_size = (1)))
model.add (Dense (8, activation = 'relu'))
model.add (Dense (1, activation = 'sigmoid'))
model.compile (loss = 'binary_crossentropy',
optimizer = 'adam', metrics = ('accuracy'))
print(model.summary())
```

#### A.2.5. Convolutional Neural Networks without Selecting Variables

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 1, 16)	384
max_pooling1d (MaxPooling1D)	(None, 1, 16)	0
dense (Dense)	(None, 1, 8)	136
dense_1 (Dense)	(None, 1, 1)	9
Total params: 529		
Trainable params: 529		
Non-trainable params: 0		

#### A.2.6. Convolutional Neural Networks after Selection by CHAID

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 1, 16)	160
max_pooling1d (MaxPooling1D)	(None, 1, 16)	0
dense (Dense)	(None, 1, 8)	136
dense_1 (Dense)	(None, 1, 1)	9
Total params: 305		
Trainable params: 305		
Non-trainable params: 0		

#### A.3. Setting a Callback Function to Store the Dynamic Training Process of Models

```
TensorBoard = TensorBoard (log_dir = 'file name', histogram_freq
= 2)
```

#### A.4. Training Models, Using the Validation Dataset for Validation and Storing the Process in the Callback Function

```
history = model.fit (x_train, y_train, epochs = 150, batch_size = 4,
validation_split = 0.15, callbacks = (TensorBoard)).
```

#### A.5. Assessing Models Based on the Test Dataset

```
t_loss,t_acc = model.evaluate (x_test, y_test)
```

*A.6. CHAID (The IBM SPSS Modeler is Utilized to Conduct CHAID in this Study, which is Very Easy to Operate and no Coding Required. The IBM SPSS Modeler is Simpler, more Convenient and Powerful for Users.)*

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
groupIndependent_data =
pd.read_excel("Independent_data.xlsx")
Response = pd.read_excel ("Response.xlsx")
X_train, X_test, y_train, y_test =
train_test_split(Independent_data,Response,test_size =
0.3,random_state = 42)
train_data = pd.concat ((X_train,y_train), axis = 1)
test_data = pd.concat ((X_test,y_test),axis = 1)
from CHAID import Tree
tree = Tree.from_pandas_df (test_data, dict (zip
(X_train.columns.tolist (), list (np.repeat('nominal',
len(X_train.columns))))), y_train.columns (0), max_depth = 10,
min_child_node_size = 3)
tree.print_tree ()
tree.classification_rules ()
```