

Analysis

The nonprofit foundation Alphabet Soup needed help selecting applicants that would have the best chance of success in their ventures. We used machine learning and neural networks to create a tool that can help predict which applicants would be successful out of a table of 34,000 organizations.

	EIN	NAME	APPLICATION_TYPE	AFFILIATION	CLASSIFICATION	USE_CASE	ORGANIZATION	STATUS	INCOME_AMT	SPECIAL_CONSIDERATIONS	ASK_AMT	IS_SUCCESSFUL
0	10520599	BLUE KNIGHTS MOTORCYCLE CLUB	T10	Independent	C1000	ProductDev	Association	1	0	N	5000	1
1	10531628	AMERICAN CHESAPEAKE CLUB CHARITABLE TR	T3	Independent	C2000	Preservation	Co-operative	1	1-9999	N	108590	1
2	10547893	ST CLOUD PROFESSIONAL FIREFIGHTERS	T5	CompanySponsored	C3000	ProductDev	Association	1	0	N	5000	0
3	10553066	SOUTHSIDE ATHLETIC ASSOCIATION	T3	CompanySponsored	C2000	Preservation	Trust	1	10000-24999	N	6692	1
4	10556103	GENETIC RESEARCH INSTITUTE OF THE DESERT	T3	Independent	C1000	Heathcare	Trust	1	100000- 499999	N	142590	1

Results

Data Preprocessing

- First, we eliminate columns that do not provide any benefits, such as "EIN" and "NAME."
- The remaining columns are considered as the features used in the model.
- Next, we divide the data into separate sets for testing and training the model.
- The target variable is denoted as "IS_SUCCESSFUL" with a value of 1 indicating "yes" and 0 indicating "no."
- The application data is analyzed while the classification data is used for binning.
- Then, we encoded the categorical variables with `get_dummies()`.

Compiling, Training, and Evaluating the Model

- In order to determine the optimal number of neurons, layers, and activation functions, we employed Keras Tuner.
- For our neural network models, we utilized three layers.
- The number of hidden nodes was determined by the number of features.

```
# Define the model - deep neural net, i.e., the number of input features and hidden nodes for each layer.
number_input_features = len( X_train_scaled[0])
hidden_nodes_layer1=7
hidden_nodes_layer2=14
hidden_nodes_layer3=21

nn = tf.keras.models.Sequential()

# First hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer1, input_dim=number_input_features, activation='relu'))

# Second hidden layer
nn.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation='relu'))

# Output layer
nn.add(tf.keras.layers.Dense(units=1, activation='sigmoid'))

# Check the structure of the model
nn.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 7)	315
dense_4 (Dense)	(None, 14)	112
dense_5 (Dense)	(None, 1)	15

=====
Total params: 442
Trainable params: 442
Non-trainable params: 0

- By implementing these three layers, we obtained 442 parameters, resulting in an accuracy of 72%.

```
[47] # Evaluate the model using the test data
model_loss, model_accuracy = nn.evaluate(X_test_scaled,y_test,verbose=2)
print(f"Loss: {model_loss}, Accuracy: {model_accuracy}")

268/268 - 0s - loss: 0.5536 - accuracy: 0.7226 - 348ms/epoch - 1ms/step
Loss: 0.5535905361175537, Accuracy: 0.7225655913352966
```

Optimization and Summary

- To optimize results and attempt to reach at least 75% accuracy, we tried only removing the “EIN” column and keeping the “NAME” column.
- By doing this, we reached 841 params and 76% accuracy.
- In summary, keeping the “NAME” column proved to be beneficial in optimizing the model to improve performance.

✓
0s

```
[44] # Evaluate the model using the test data
      model_loss, model_accuracy = nn.evaluate(X_test_scaled,y_test,verbose=2)
      print(f"Loss: {model_loss}, Accuracy: {model_accuracy}")
```

```
268/268 - 0s - loss: 0.4843 - accuracy: 0.7643 - 436ms/epoch - 2ms/step
Loss: 0.4842992126941681, Accuracy: 0.7643148899078369
```