**Introduction**

**Purpose of the Analysis**

The purpose of this analysis is to build a predictive model to determine the effective use of charity donations. By analyzing historical data of past donations, we aim to create a neural network model that can predict whether a donation will be successful utilized based on various features. The primary goal is to achieve a model accuracy of at least 75% to help the charity optimize their philanthropic strategies.

**Data Preprocessing**

**Target Variable**

The target variable for our model is IS\_SUCCESSFUL, which indicates whether a donation was successful.

**Feature Variables**

The feature variables for our model include all other columns in the dataset except for the non-beneficial ID columns. Specifically, these features include:

* APPLICATION\_TYPE
* AFFILIATION
* CLASSIFICATION
* USE\_CASE
* ORGANIZATION
* STATUS
* INCOME\_AMT
* SPECIAL\_CONSIDERATIONS
* ASK\_AMT

**Variables to Remove**

The columns EIN and NAME were removed from the input data because they are neither targets nor features and do not provide meaningful information for the prediction task.

**Compiling, Training, and Evaluating the Model**

**Neural Network Model Structure**

Neurons, Layers, and Activation Functions

The final neural network model was constructed with the following structure:

1. Input Layer: 43 input features.
2. First Hidden Layer: 256 neurons, ReLU activation function, followed by a 50% dropout layer.
3. Second Hidden Layer: 128 neurons, ReLU activation function, followed by a 50% dropout layer.
4. Third Hidden Layer: 64 neurons, ReLU activation function, followed by a 30% dropout layer.
5. Fourth Hidden Layer: 32 neurons, ReLU activation function, followed by a 30% dropout layer.
6. Fifth Hidden Layer: 16 neurons, ReLU activation function, followed by a 20% dropout layer.
7. Output Layer: 1 neuron, sigmoid activation function.

The selection of neurons and layers was based on experimentation to balance model complexity and performance. ReLU activation functions were chosen for hidden layers to introduce non-linearity, while the sigmoid activation function was used in the output layer for binary classification.

**Model Performance**

The model was trained with an early stopping callback and learning rate reduction. The model training stopped after 29

epochs due to early stopping, indicating no improvement in validation loss. The highest accuracy achieved was below the target of 75%.

**Steps Taken to Increase Model Performance**

Several steps were taken to improve model performance:

1. Data Preprocessing: Removed non-beneficial columns, replaced infrequent categories with "Other", and converted categorical data to numeric using pd.get\_dummies.
2. Model Complexity: Increased the number of layers and neurons in the network.
3. Regularization: Added dropout layers to prevent overfitting.
4. Learning Rate Adjustment: Used the ReduceLROnPlateau callback to reduce the learning rate when the model stopped improving.
5. Early Stopping: Implemented early stopping to avoid overfitting and to restore the best weights observed during training.

Despite these efforts, the model did not reach the desired accuracy level.

**Overall Results and Alternative Approaches**

**Summary of Results**

The final model, despite various optimizations, did not achieve an accuracy above 75%. The best performance was around 72%, indicating that further improvements or different modeling techniques may be necessary.

**Alternative Model**

To potentially achieve better performance, a different model such as a Random Forest or Gradient Boosting Machine (GBM) could be used. These models are effective for classification tasks and can handle both linear and non-linear relationships well. Additionally, they provide feature importance metrics which can be useful for understanding the impact of different features on the prediction outcome.

**Advantages of Alternative Model**

* Random Forest: Offers robustness to overfitting, handles large feature spaces well, and provides feature importance scores.
* Gradient Boosting: Often achieves high performance with careful tuning, can handle complex data patterns, and provides robust predictive power.

**Conclusion**

The neural network model, after several optimizations, did not meet the target performance. Exploring alternative models such as Random Forest or Gradient Boosting could potentially provide better accuracy and insights. Further tuning and feature engineering might also help in improving model performance.

By leveraging these insights and alternative modeling techniques, the charity can better predict donation success and optimize their fundraising strategies.