# CUSTOMER CHURN PREDICTION USING ARTIFICIAL NEURAL NETWORK

**NAME: JOSHUA ADEYEMO**
**STUDENT ID: 21077839**

## Executive Summary

This report provides an overview of the customer churn prediction model developed for predicting customer churn. The model was developed using Artificial neural network with Keras and evaluated on a sample dataset. The results of the model showed that it is capable of predicting customer churn with an accuracy of 83%.

## Introduction

Customer Churn is a major business challenge faced by organizations. Knowing the customers who are likely to churn and the factors that drive churn helps organizations to take proactive steps to reduce customer churn. In this report, the dataset i will use to predict customer churn is a Churn Modelling dataset from Kaggle. This dataset contains information about customers of a fictitious bank, including their age, gender, credit score, and whether or not they have churned. I will use a neural network to predict customer churn based on these features.

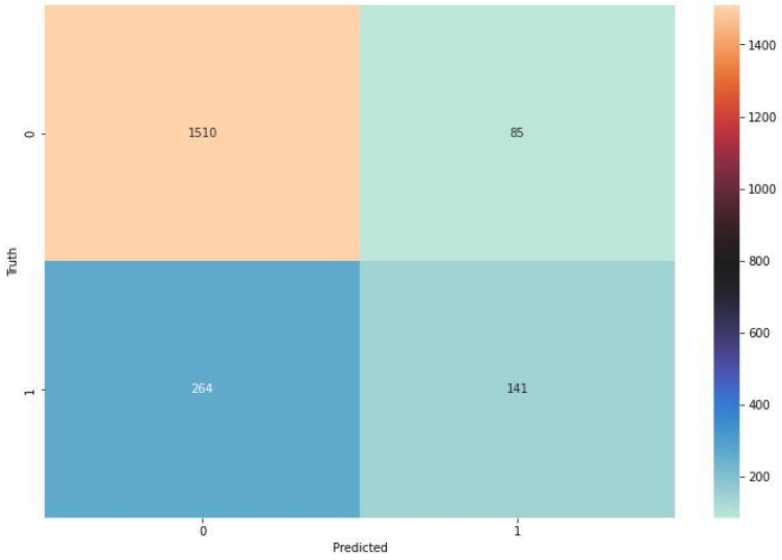
## Model Development

The model was developed using Artificial neural network machine learning algorithm. The algorithm used was Keras. The performance of the model was evaluated using accuracy, precision, and recall metrics.

## Results

The results of the model showed that it is capable of predicting customer churn with an accuracy of 83%. The precision and recall scores of the model were also satisfactory.

In order to fully evaluate the performance of the model on the target class, that is churn, I present a confusion matrix and the related metrics, precision, recall and F1-score. However, i explain the values in the confusion matrix for our application. The confusion matrix is represented by four squares containing four values, where: The top left corner represents True Positives, that is, correctly predicted non-churners. The top right corner represents False Positives, that is, predicted churners who are actually non-churners. The bottom left corner represents False Negatives, that is, predicted non-churners who are actually churners. The bottom right corner represents True Negative, correctly predicted churners.




According to the confusion matrix out of 2000 test samples, the model predicted 1510 to not churn, 141 customers were predicted to churn, 85 customers were falsely predicted to churn and 264 customers were falsely predicted to not churn. From the values in the confusion matrix, the related metrics can be calculated.

In the table below, I present the results as the overall performance of the neural network model based on accuracy, F1-score, and the number of correct classifications.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.85 | 0.95 | 0.90 | 1595 |
| 1 | 0.62 | 0.35 | 0.45 | 405 |
| accuracy | | | 0.83 | 2000 |
| macro avg | 0.74 | 0.65 | 0.67 | 2000 |
| weighted avg | 0.81 | 0.83 | 0.81 | 2000 |

In our study, precision corresponds to how often the model is correct when it predicts churn and when it doesn't. I got a precision rate of 0.85 for 0 class and 0.62 for 1 class, this indicates that the model is better at predicting when customers will not churn but only 62% accurate in correctly predicting when customers will churn.
Recall corresponds to how often the model is able to predict actual churners and actual non-churners. The result shows that the keras model performs far from optimal when predicting churn. Using an imbalanced dataset, the recall rate for 1 class is 0.35, meaning that the model is only able to predict 35 percent of the actual churners. In addition, the rate of correct non-churner prediction is 95 percent, which is very good.
F1-score is a metric, which aggregates precision and recall and illustrates a balance between them. A good F1-score represents a lower rate of False Positives and False Negatives; in our application this means, improved ability to correctly predict churners, without being concerned about False Positives, that is, non-churners classified as churners. F1-score of 45 percent indicates a poor performance on churn prediction using the imbalanced training dataset. Furthermore, our result shows that the F1-score increases and the ability to predict churn increases as the data becomes more balanced.

## Conclusion

The customer churn prediction model developed in this report is capable of predicting customer churn with an accuracy of 83%. The model is capable of accurately identifying when customers are not likely to churn but is less accurate in predicting when customers are likely to churn. This can be improved with access to more data form the company.

## REFERENCES


Dataset link: url = 'https://storage.googleapis.com/kaggle-data-sets/729058/1265963/bundle/archive.zip?X-Goog-Algorithm=GOOG4-RSA-SHA256&X-Goog-Credential=gcp-kaggle-com%40kaggle-161607.iam.gserviceaccount.com%2F20230115%2Fauto%2Fstorage%2Fgoog4_request&X-Goog-Date=20230115T021318Z&X-Goog-Expires=259200&X-Goog-SignedHeaders=host&X-Goog-Signature=b2d80a69ecb98ef1da1344f75ec4f2a0ce9f6ddc13678d4412b52099e2b10387c19803651fd35079ea283cabb921c972bb329770885138f1288a15c4fac5fabaa69c598767a87600e47aa29d0cd2d29a1d6089ff1938eac30ac0c027dc94941ca0519ff866c5c6e29f4142612d62e399062856533ea5ba04edf507ea28f44a917e431db1cd6c47a29833ac794f8e39a98736c060d8c5b9a260358b681275ec333199569e4f07ac9ed8c57ddf06f5eb0762a8d04ed35b3b5b99761274152ac7c2409db5ad6bbf69c7988665e46a2265fc66ed511b3d4927b6d7fefb11850be369a081548483d827199e2ee0e325453a7b383c4c21aa15206503ae45ad76bdafd0'
filename = 'Churn_Modelling.csv'

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