Bank Churn Prediction

NNL project and AIML

2/7/2025

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Contents / Agenda

- Executive Summary
- Business Problem Overview and Solution Approach
- EDA Results
- Data Preprocessing
- Model Performance Summary
- Appendix

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Executive Summary

- There are less female customers than male customers. There is a 10% point difference. Have a plan to market to female population as well.
- France is 25% points better than Germany and Spain. Check what is working and what is working well in France and try to implement the same strategies in Germany and Spain.
- 30% of the Customers does not have credit cards, some improvements could be made to sell Credit Cards to existing customers instead of trying to get new credit card customers. Do this might reduce your customer acquisition cost. Also customers having more than two products from the bank usually stays as a customer.

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Business Problem Overview and Solution Approach

Problem

To build a neural network-based classifier that can determine whether a customer will leave the bank or not in the next 6 months.

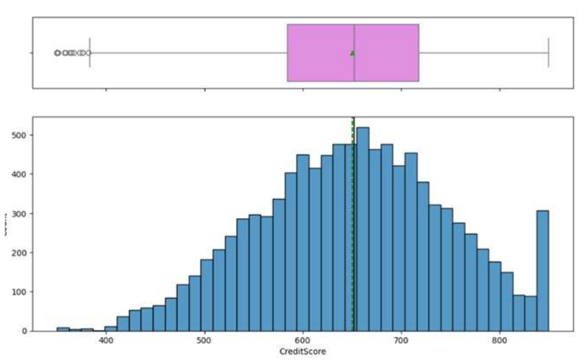
Solution and Methodology:

This requires clear understanding of the classification of the categories in the given data set. For better understanding, we need to study the data set based on each column(univariate) , comparison of two columns (Bi variate), and finally overall relation of data with each other(multi variate).

From this inference business promotion, strategies , customer engagement , operational improvement and feed back handling needs to be carried out.

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

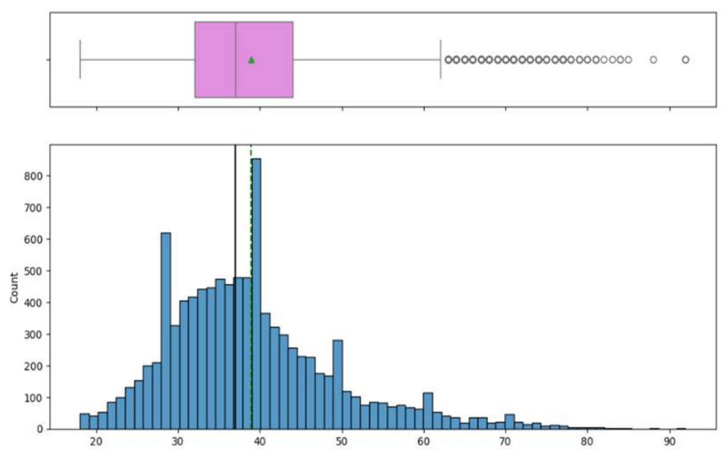
EDA Results



Observation

•Credit Score is very slightly left skewed.

•There are few outliers with low credit scores.



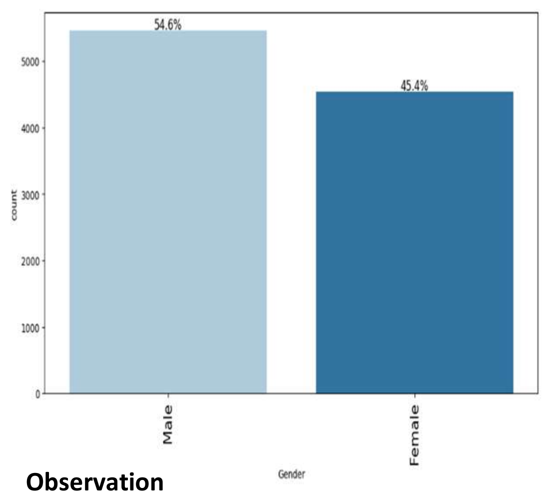
Observation

•Age is skewed to the right.

•There are outliers for age.

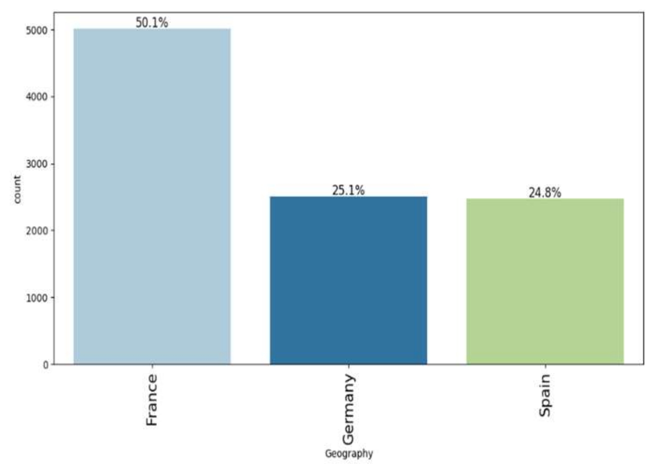
Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

EDA Results



Observation

•In this dataset, 54% of the observations are Male

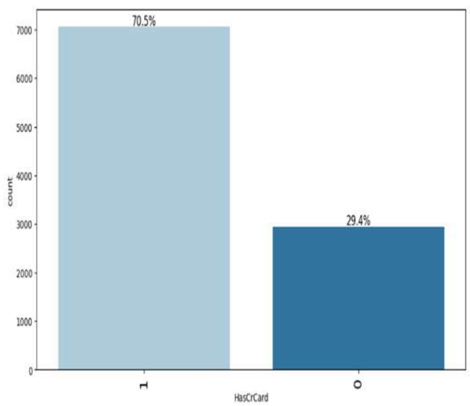


Observation

•In this dataset, 50% of the observations are from France
•In this dataset, 25% of the observations are from Germany and rest from Spain.

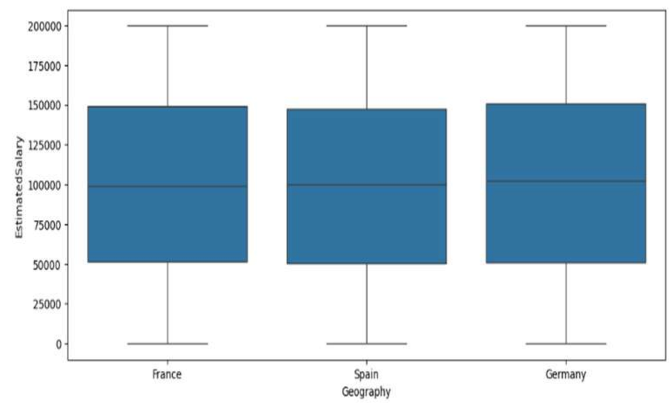
Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

EDA Results



Observation

•In this dataset, 70% of the population have Credit Card

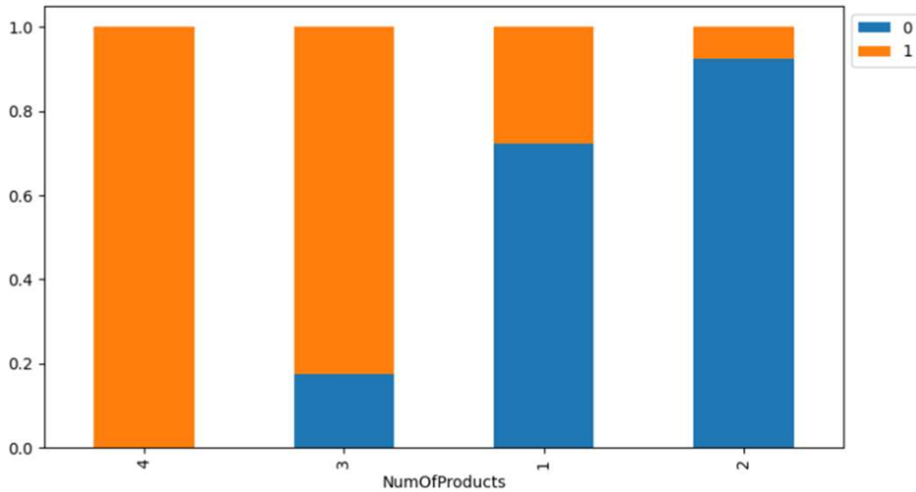


Observation

•The Estimated Salary looks the same across all locations

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

EDA Results

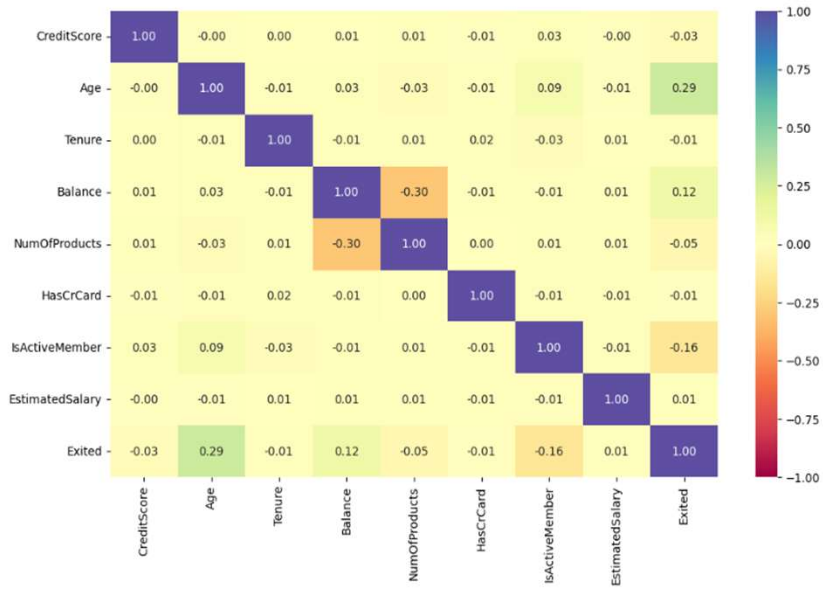


Observation

•Customers having 3 or more products have stayed longer.
•Customers with 4 products has zero Exited

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

EDA Results



Observation

•There are no strong negative or positive correlation

•There is a slight correlation between Age of the customer and Exited feature.

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Preprocessing

```
Feature 'CreditScore' has 460 unique value(s).
Feature 'Geography' has 3 unique value(s).
Feature 'Gender' has 2 unique value(s).
Feature 'Age' has 70 unique value(s).
Feature 'Tenure' has 11 unique value(s).
Feature 'Balance' has 6382 unique value(s).
Feature 'NumOfProducts' has 4 unique value(s).
Feature 'HasCrCard' has 2 unique value(s).
Feature 'IsActiveMember' has 2 unique value(s).
Feature 'EstimatedSalary' has 9999 unique value(s).
Feature 'Exited' has 2 unique value(s).
```

- ″Gender″ column is one-hot encoded into Gender_Male.
- "Geography″ column is one-hot encoded into Geography _Germany and Geography_Spain. The first city category is dropped

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	Geography_Germany	Geography_Spain	Gender_Male
0	619.0	42.0	2.0	0.00	1.0	1.0	1.0	101348.88	1.0	0.0	0.0	0.0
1	608.0	41.0	1.0	83807.86	1.0	0.0	1.0	112542.58	0.0	0.0	1.0	0.0
2	502.0	42.0	8.0	159660.80	3.0	1.0	0.0	113931.57	1.0	0.0	0.0	0.0
3	699.0	39.0	1.0	0.00	2.0	0.0	0.0	93826.63	0.0	0.0	0.0	0.0
4	850.0	43.0	2.0	125510.82	1.0	1.0	1.0	79084.10	0.0	0.0	1.0	0.0

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Preprocessing

```
Out[ ]:
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

	count	mean	std	min	25%	50%	75%	max
RowNumber	10000.0	5.000500e+03	2886.895680	1.00	2500.75	5.000500e+03	7.500250e+03	10000.00
CustomerId	10000.0	1.569094e+07	71936.186123	15565701.00	15628528.25	1.569074e+07	1.575323e+07	15815690.00
CreditScore	10000.0	6.505288e+02	96.653299	350.00	584.00	6.520000e+02	7.180000e+02	850.00
Age	10000.0	3.892180e+01	10.487806	18.00	32.00	3.700000e+01	4.400000e+01	92.00
Tenure	10000.0	5.012800e+00	2.892174	0.00	3.00	5.000000e+00	7.000000e+00	10.00
Balance	10000.0	7.648589e+04	62397.405202	0.00	0.00	9.719854e+04	1.276442e+05	250898.09
NumOfProducts	10000.0	1.530200e+00	0.581654	1.00	1.00	1.000000e+00	2.000000e+00	4.00
HasCrCard	10000.0	7.055000e-01	0.455840	0.00	0.00	1.000000e+00	1.000000e+00	1.00
IsActiveMember	10000.0	5.151000e-01	0.499797	0.00	0.00	1.000000e+00	1.000000e+00	1.00
EstimatedSalary	10000.0	1.000902e+05	57510.492818	11.58	51002.11	1.001939e+05	1.493882e+05	199992.48
Exited	10000.0	2.037000e-01	0.402769	0.00	0.00	0.000000e+00	0.000000e+00	1.00

Observation:

There are 21 features and 10127 observations

• There are no missing values

There are no duplicate values in the data.

customerid should not be a numeric value.

•Avg age of the customers is 38

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

With the data distribution into training and validation, the best metric for this business scenario is build

```
train_metric_df = pd.DataFrame(columns=["recall"])
valid_metric_df = pd.DataFrame(columns=["recall"])
```

This metric is used under different neural network to generate the model.

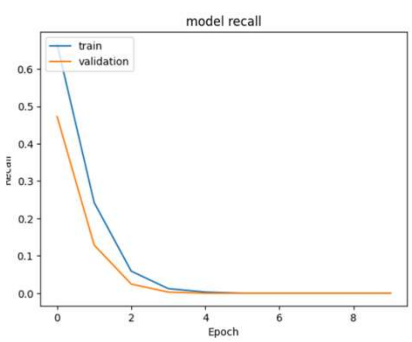
- 'Binary_crossentropy' is used as the loss function, which is appropriate for binary classification tasks.
- Recall() from tensorflow.keras.metrics is included as the metric to track recall during training.

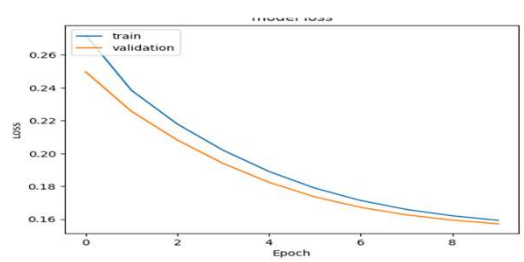
Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Preprocessing

•After processing each batch (15 samples at a time), the model updates its weights.
•This process continues for 10 epochs (or whatever number you choose).

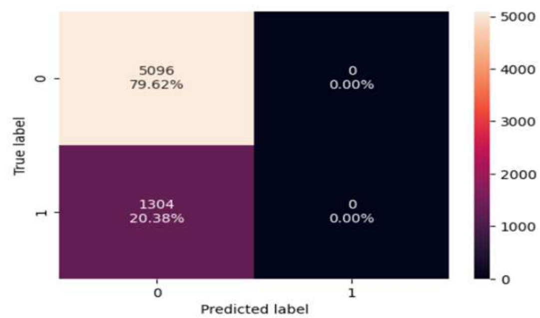
After training, you can inspect the history_0 object, which contains information about the loss and metrics (such as accuracy or recall) over each epoch, both for training and validation data. This is useful for understanding how well the model performed during training and how it generalized on the validation set.

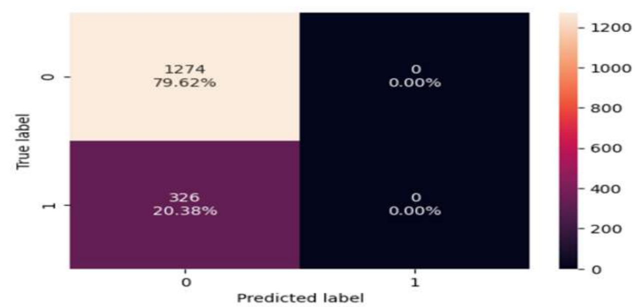




Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Preprocessing





- Accuracy (83.13%) is relatively high, but it is misleading since the model is not predicting any instances of class 1.
- Precision, Recall, and F1-Score are 0, indicating the model failed to predict any positive cases (class 1).
- Specificity is 100%, meaning the model is perfect at predicting class 0, but this isn't useful in the context of a balanced performance between both classes.

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Preprocessing

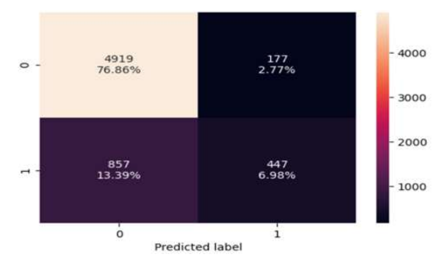
So the performance improvement is required.
It is carried with the following:

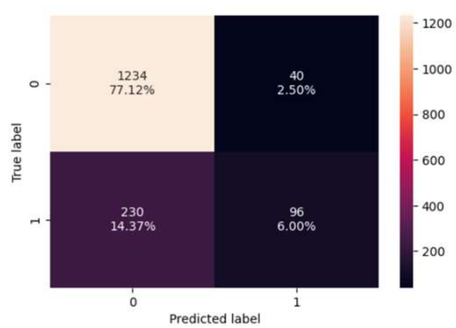
Neural Network with Adam Optimizer

- Neural Network with Adam Optimizer and Dropout
- Neural Network with Balanced Data (by applying SMOTE) and SGD Optimizer
- Neural Network with Balanced Data (by applying SMOTE) and Adam Optimizer
- Neural Network with Balanced Data (by applying SMOTE), Adam Optimizer, and Dropout

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Model Performance





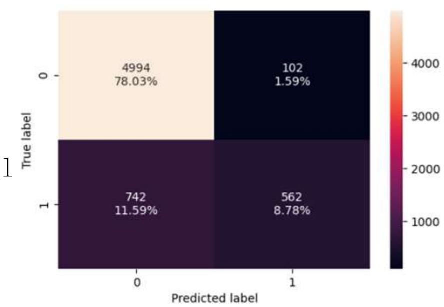
•Accuracy (83.94%) is high, but accuracy alone doesn't fully reflect model performance, especially in imbalanced datasets where one class may dominate.
•Precision (71.5%) is decent, meaning that when the model predicts class 1, it is correct most of the time, but it still makes some mistakes.
•Recall (34.2%) is low, indicating that the model is missing a significant number of true positives (class 1). This is a major issue if predicting class 1 is important.
•F1-Score (46.1%) reflects the balance between precision and recall, and it's moderate, suggesting that both recall and precision could be improved.
•Specificity (96.5%) is very high, meaning that the model is very good at predicting class 0, but this suggests a possible class imbalance or model bias toward the negative class.

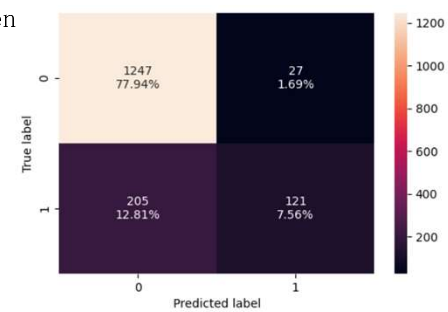
Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Model Performance

Neural Network with Adam Optimizer and Dropout

•**Accuracy (85.5%)** is high, but the model's performance may be skewed by the class imbalance.
•**Precision (81.6%)** is good, meaning that when the model predicts class 1, it is reliable most of the time.
•**Recall (37.1%)** is low, meaning the model is missing a large number of true positives (class 1). This is a concern if predicting class 1 is important.
•**F1-Score (51.2%)** reflects a moderate trade-off between precision and recall, indicating room for improvement in detecting class 1.
•**Specificity (97.9%)** is very high, showing that the model is very good at correctly predicting class 0, but this suggests a bias toward the negative class.

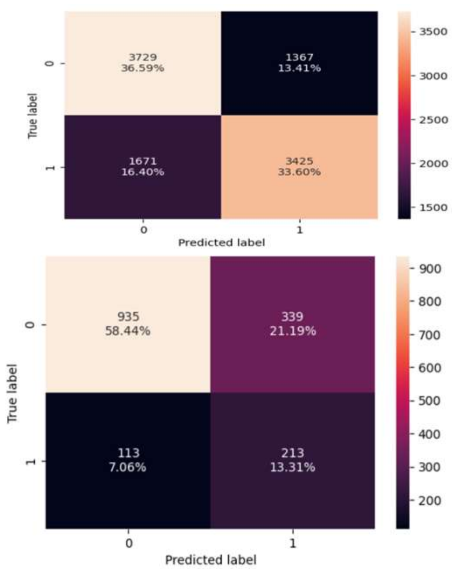




Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Model Performance

Neural Network with Balanced Data (by applying SMOTE) and SGD Optimizer



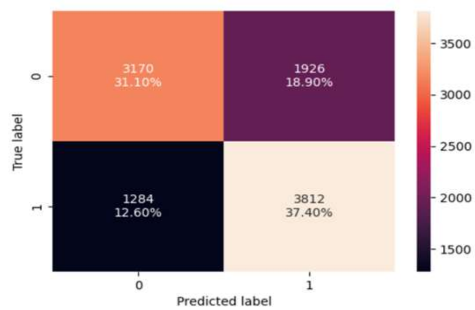
- Accuracy (71.88%) is moderate, suggesting that the model is not performing perfectly. Accuracy may be misleading here, especially if there is class imbalance.
- Precision (38.6%) is low, indicating that the model is making many false positive predictions for class 1. This means that the model's predictions for class 1 are not very reliable.
- Recall (65.3%) is better, indicating that the model is correctly identifying a good portion of class 1 instances, but still misses a significant number of them (113 false negatives).
- F1-Score (48.2%) is fairly low, reflecting the imbalanced performance between precision and recall. The model's performance is not ideal, but it is balancing precision and recall somewhat.
- Specificity (73.3%) is moderate, meaning that the model is not perfect at predicting class 0, but still performs reasonably well.

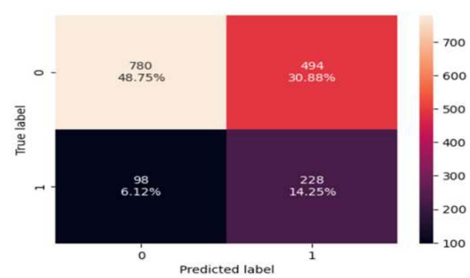
Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Model Performance Summary

Neural Network with Balanced Data (by applying SMOTE) and Adam Optimizer

•Accuracy (75.9%) is solid, showing that the model is doing well overall.
•Precision (44.4%) is moderate, suggesting that the model makes a significant number of false positives when predicting class 1. The model could be more reliable in predicting class 1 correctly.
•Recall (72.3%) is good, meaning the model is identifying a significant portion of the true positives (class 1), but it still misses 90 true positives (false negatives).
•F1-Score (55.3%) reflects a moderate balance between precision and recall. The model performs reasonably well in recall, but its precision still limits its performance.
•Specificity (76.8%) is fairly good, showing that the model is effective at predicting class 0 (negative class).

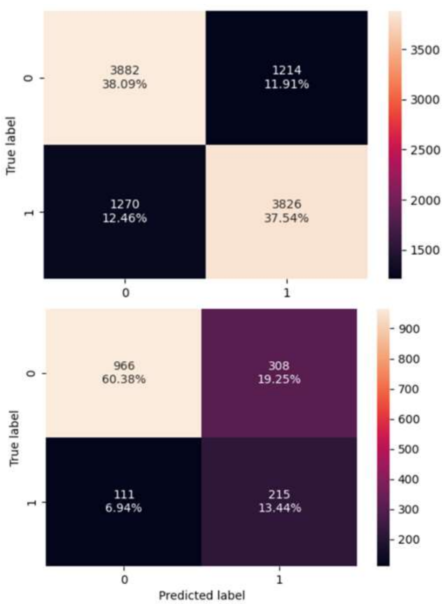




Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Model Performance

Neural Network with Balanced Data (by applying SMOTE), Adam Optimizer, and Dropout



•Accuracy (73.81%) is solid, indicating that the model is performing reasonably well overall, though there is still room for improvement.
•Precision (41.1%) is relatively low, suggesting that the model makes many false positive predictions when it classifies a sample as class 1.
•Recall (66.0%) is moderate, meaning the model is able to correctly identify a decent portion of the true positives (class 1), but still misses 111 instances.
•F1-Score (50.4%) is moderate, reflecting the balance between precision and recall. The model is decent at recalling class 1 but needs improvement in terms of precision.
•Specificity (75.9%) is relatively high, meaning the model is good at predicting class 0 correctly, but this is overshadowed by the low precision

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Model Performance Summary

Training performance comparison

	recall
NN with SGD	0.000000
NN with Adam	0.342791
NN with Adam & Dropout	0.430982
NN with SMOTE & SGD	0.672096
NN with SMOTE & Adam	0.826138
NN with SMOTE,Adam & Dropout	0.750785

Validation set performance comparison

	recall
NN with SGD	0.000000
NN with Adam	0.294479
NN with Adam & Dropout	0.371166
NN with SMOTE & SGD	0.653374
NN with SMOTE & Adam	0.785276
NN with SMOTE,Adam & Dropout	0.659509

```
train_metric_df - valid_metric_df
```

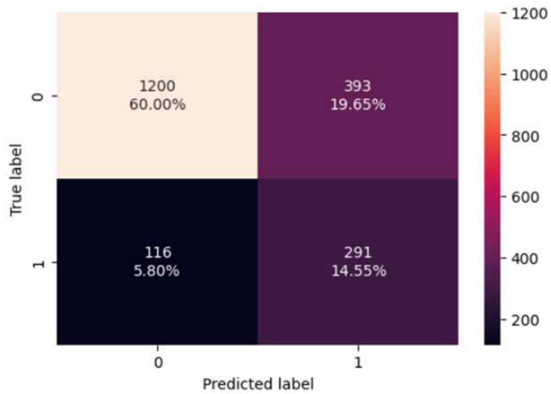
	recall
NN with SGD	0.000000
NN with Adam	0.048313
NN with Adam & Dropout	0.059816
NN with SMOTE & SGD	0.018722
NN with SMOTE & Adam	0.040862
NN with SMOTE,Adam & Dropout	0.091276

The comparison of the model is listed here. This chart will help us to predict the model that fit the business requirement.
Here in this process there are five different models are generated.
And then the data is compared to validate the best suited model.
With the given comparison, it is clear the model five with Neural Network with Balanced Data (by applying SMOTE) and Adam Optimizer
Is best.

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Model Performance Summary

	precision	recall	f1-score	support
0.0	0.91	0.75	0.83	1593
1.0	0.43	0.71	0.53	407
accuracy			0.75	2000
macro avg	0.67	0.73	0.68	2000
weighted avg	0.81	0.75	0.77	2000



•Accuracy (74.55%) is solid, showing that the model is performing reasonably well overall.
•Precision (42.6%) is moderate, suggesting that the model makes a fair number of false positives when predicting class 1. Improving precision is important to reduce the number of false positives.
•Recall (71.6%) is good, meaning that the model is identifying a significant portion of the true positives (class 1), but still misses 116 true positives (false negatives).
•F1-Score (53.1%) reflects a moderate balance between precision and recall. The model is stronger in recall but could be more precise in its class 1 predictions.
•Specificity (75.4%) is fairly high, indicating that the model is good at identifying class 0 (negative class) instances.

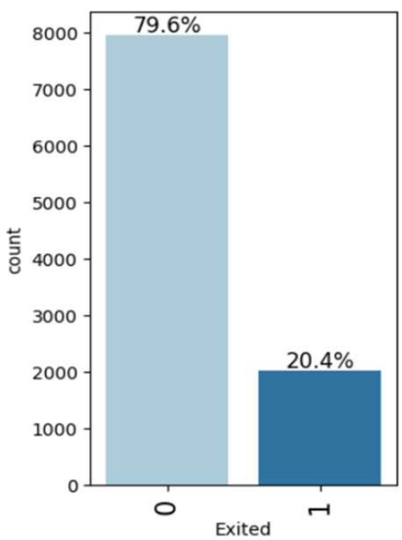
Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

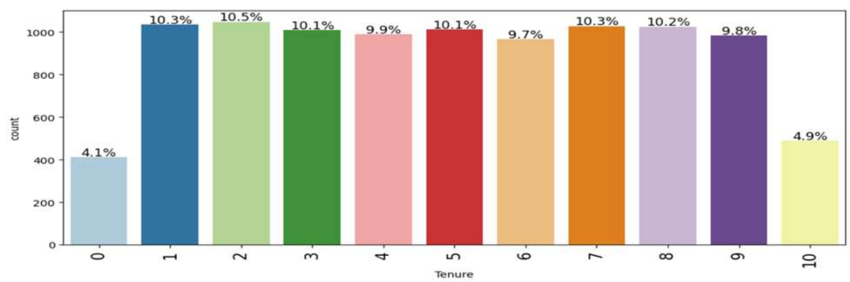
Great Learning
POWER AHEAD

APPENDIX

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Background and Contents

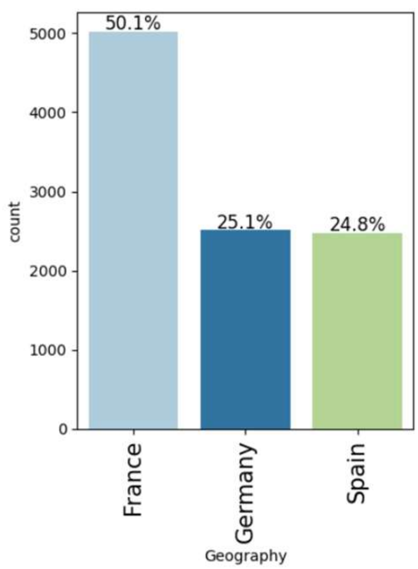




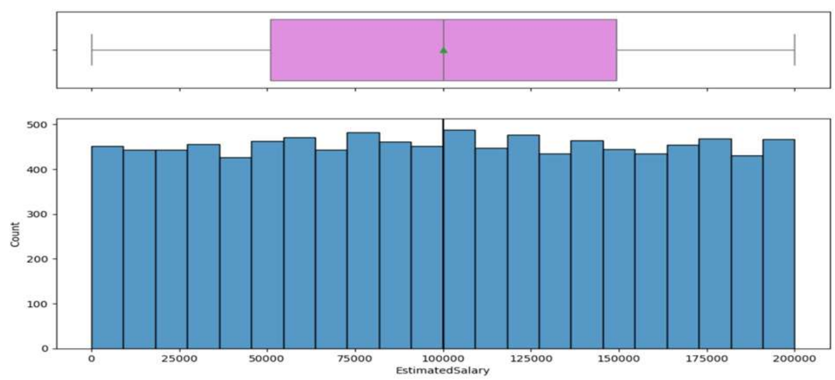
Tenure: Number of years for which the customer has been with the bank.
With 5yr and above the tenure, is high enough. With zero tenure and Ten yrs
are the least in the collected data set.

Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Background and Contents

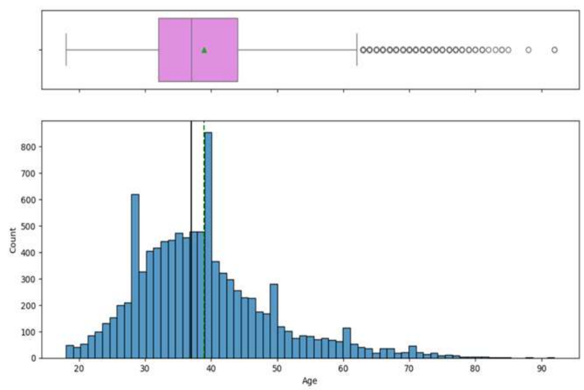


France has the max count among the other countries Like Germany and Spain.
The data shows the zero salary .
Those data needs to be handled.

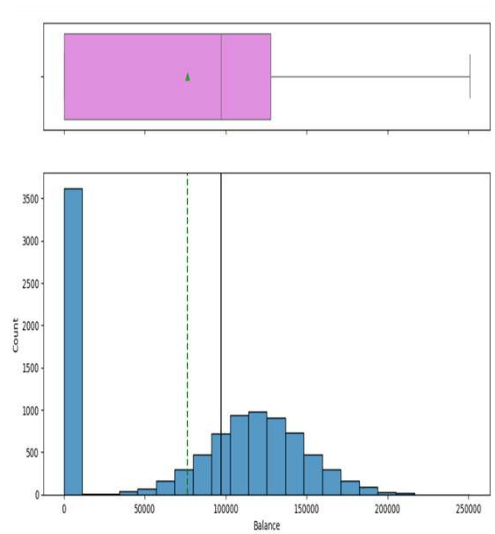


Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Data Background and Contents



There are more outlier on the data set. At the age of around 40 yrs, the count is more. The data shows that with the age the customer are less.



Proprietary content. © Great Learning. All Rights Reserved. Unauthorized use or distribution prohibited.

Great Learning

Happy Learning !

27