Customer Churn Prediction Model Using Artificial Neural Networks (ANN): A Case Study in Banking

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Abstract— **Customer Churn has a great impact on banking industries as it accelerates a loss of revenue and customer loyalty. The focus of the research is to create a model for the banking sector using Artificial Neural Networks (ANNs) which can predict if the customer will churn. The prediction is based on the input features and the independent variable of the trained dataset. The hyperparameters are altered during model training using the forward propagation algorithm and cross-validation techniques which enable the model to perform well with respect to accuracy and precision rate. The achieved results illustrate that the suggested model has an accuracy of 86% at predicting customer attrition. In comparison to the logistic regression model outcomes, ANN models are more effective for predicting customer churn in the banking industry. The study suggests vital perceptions of how to employ machine learning approaches to increase client retention and decrease customer churn. Banks can use this model to spot clients who are at risk of churning and take proactive measures to keep them.**

Keywords— Churn prediction, ANN, Machine Learning, Customer Retention, Banking.

I. INTRODUCTION

Customer churn is considered one of the significant issues facing the banking sector, and keeping clients is essential to the success of the company. Customer churn is the process through which clients stop doing business with one bank and switch to another [1]. Banks now depend heavily on churn prediction algorithms to predict and stop client churn. Customer Churn Prediction is a type of Client Relationship Management (CRM) where an organization develops a model that forecasts whether a customer is intending to leave or reduce its purchases from a company [2]. Different businesses utilize prediction techniques based on Machine Learning. Artificial Neural Networks (ANN) have emerged as a viable method for creating churn prediction models with the development of powerful machine learning techniques. Since acquiring new consumers is a costly endeavor, it makes sense for businesses to anticipate and work to retain existing clients [3]. In order to construct a predictive model to identify consumers who are at risk, the study attempts to shed light on the elements that affect client churn in the banking industry. Additionally, the study will examine the performance of ANN models with those of conventional machine learning models and offer suggestions for churn prediction model accuracy improvement.

II. LITERATURE REVIEW

A. Customer Churn and Retention in Banking

Customer churn rate is commonly used as a measure of customer loss. Due to the increasing competition between public and private banks, the industry often loses productive customers, and as a result, revenues are lost. It has been a long time since banking underwent such a profound change. As a result of deregulation, different services have been added, technology has advanced, and there is more competition in the market [4]. Managing customer churn and improving customer relationship management (CRM) is essential for banks so they are able to protect their loyal customers, ensure growth, and improve customer service. [5]. Banks face one of the most difficult challenges when it comes to retaining churn-prone customers. In the current market, customers have a variety of options for churning due to the increase in banking service providers and the increasing level of competition. Consequently, bank management is becoming more aware of the value of keeping current customers [6], [7], [3].

Technology advancements, globalization, and the advent of fintech are factors that affect customer turnover in the banking sector [4]. These factors have increased competition in the market for financial products and services. In addition to these elements, the emergence of social networks and mobile technology, which increased customers' access to information, contributed to the improvement of customer financial awareness [8]. These circumstances have lowered their allegiance to the various banks with whom they currently transact business and raised their expectations for the quality of the goods and services they consume [8].

B. Churn Prediction Models

Churn prediction models have been the subject of extensive research. The binary classification task is a technique used by organizations to estimate client attrition [9]. The query of whether a customer would leave the business within a given time frame is entered into the binary classification task as an input, and the result is either yes or no which is represented by 1 or 0 respectively [9].

The most widely used techniques include logistic regression, decision trees, neural networks, support vector machines, and survival analysis [10],[11],[12],[13].

The researcher built a predicted churn model, and 12 classification algorithms were applied in the study to a dataset of actual credit cardholders' behavior from a major Chinese commercial bank [14].

The author in [15] was eager to find out what factors affect employee attrition in businesses. He used gradient boosting models to forecast the "Turnover status." The model lacks prescriptiveness but is deductive. It is not compared to a more reliable machine learning strategy such as deep neural networks [16].

The research work [17] used a NN to predict the exhaustion of customer in cellular service. Data features such as age, gender, consumer status (retired, student, employed, unemployed), average monthly income, and whether the client uses 2 or more products were used as control variables for NN.

Author [18] put forth a brand-new approach for measuring and forecasting client attrition in the banking sector that made use of artificial neural networks. Authors in [19] have conducted a study on the impact of "Employ Satisfaction" on employee churn in which Regression techniques were adopted as the methodology for their research paper. Unfortunately, machine learning techniques were not adopted for churn prediction and feature extraction and validation process. They have implicitly declared that employee attrition is significantly influenced by employee satisfaction. At the same time, authors in [20] have come up with another study where they have predicted customer churn using machine learning techniques. Their method of study was different from the previous methods where they introduced the ML models such as support vector, and decision tree. This was backed by the research of the author [21] who applied a support vector machine on structural risk minimization to enhance the machine learning method's predictive capabilities. In comparison to ANN, decision trees, logistic regression, and naive Bayesian classifiers, the findings demonstrated that the support vector machine method has a reliable accuracy rate, hit rate, covering rate, and lift coefficient [22].

The following Table I illustrates the summary of more churn prediction models:

TABLE I. SUMMARY OF CHURN PREDICTION MODELS

Author	Dataset	Model	Findings
K.G.M Karvana et al. (2019)	XYZ Bank of Indonesia. Tested 5 different classification methods with 57 attributes.	Vector Machine (SVM)	The best method is a support Vector Machine (SVM) with a comparison of 50:50 Class sampling data is the best method for predicting churn customers at a private bank in Indonesia.
K. Mishra and R. Rani (2017)	IBM Watson Analytics. 7,043 Instances 21 attributes. 4 numerical and 17 nominal attribute	Logistic Regression, ANN, and Random Forest	SMOTE (Synthetic Minority Over-Sampling Technique) is one of the most adopted approaches due to its simplicity and effectiveness. Co-relation and ensembling perform well for predicting churners as against simply applying learners on the unrefined dataset
X. Wang et al. (2020)	Kaggle dataset. 99 features worth concern. 100,000 instances along with an indication of whether or not that customer churned.	LR, XGBoost, and Decision Tree	Based on model performance, the top four models are Light Random GBM, XGBoost, Forest, and Decision Tree and Logistic Regression, which achieved 0.6830, 0.6800, 0.6442 and 0.6382. Light GBM and XGBoost are performing similarly well in terms of AUC score, Light GBM is more efficient
B. He, Y. Shi, Q. Wan, and X. Zhao (2014)	Customer dataset by a Chinese commercial bank	SVM model Logistic regression model for comparison	no matter what the sampling ratio is, the prediction effect of RBF SVM is optimal. The SVM model can predict churners effectively and has relatively high accuracy. The data of the customer churn for commercial banks often display imbalanced features. Hence, combine the random sampling method with the SVM model and select the appropriate kernel to improve customer churn prediction effectively.
Kim and Yoon (2004)	A sample of 973 subscribers belonging to the five mobile carriers in Korea	Logistic Regression	Longer subscription terms are typically linked to a decreased likelihood of turnover. This simply means that a consumer is more likely to stick with a cell carrier the longer they have a subscription.
Buckinx and Poel, (2005)	Retailing dataset	Neural Network and Logistic Regression	The greatest predictors of partial customer defection, similar to direct marketing applications, are historical behavioral indicators, more specifically RFM variables (recency, frequency, monetary value).

C. Artificial Neural Networks

Artificial Neural Networks (ANN) is defined as the “Data processing system consisting of a large number of simple, highly interconnected processing elements in an architecture inspired by the structure of the cerebral cortex of the brain” [23]. An ANN is a sophisticated network made up of a lot of simple nodes called neural cells [17]. A model for information processing called a neural network takes inspiration from organic nerve systems like the brain. It can draw lessons from the past, just like individuals do. Since ANNs contain neural cells and memory, they can store and interpret past knowledge which may be unclear, nonlinear, and noisy, without any mathematical models to determine patterns [17].

Input, output, and hidden layers make up a conventional feed-forward multi-layer perceptron neural network. Neural networks can be separated into single-layer perception (SLR) and multilayer perception (MLP) networks [3]. There may be one or more hidden layers of neurons in between. Such in-between levels are called hidden layers and nodes contained in these layers are called hidden nodes as these are not taking inputs directly from outside [32]. Each connection has a weight assigned to each other [24]. Figure 2 illustrates the architecture of Artificial Neural Networks:

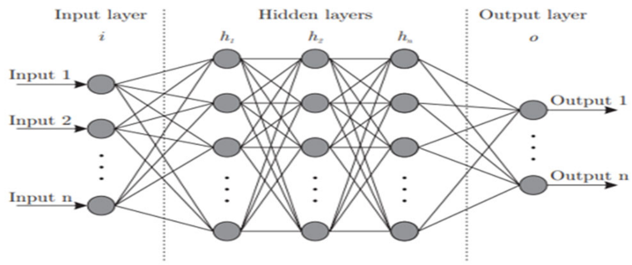

Fig 2. Artificial Neural Networks Architecture [25].

III. METHODOLOGY

The study was conducted using an open-sourced dataset named Churn Modelling, which was taken from the Kaggle website. The data was pre-processed with data cleaning, data transformation, feature selection, feature scaling, and data splitting into train and test sets. The trained machine learning model will be evaluated using the performance matrices. If the proposed model is not performed well, it has to undergo certain model optimization techniques so as to get the expected results. ANN model is intended to predict whether the customer is churned or not in banking domain. In this paper, machine learning has been performed for the prediction of customer churn in the banking industry. Figure 3 illustrates the procedures for building the ANN model.

A. Data Collection

The dataset is publicly available [34], it includes various features and details of a bank's customers such as demographic information, transaction history, and customer behavior.

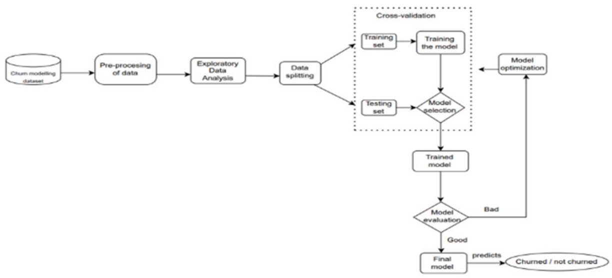

Fig 3. A Model of Predicting Customer Churn

Some main features that are included in the dataset are:

- Customer demographic information: age, gender, geography, etc.,
- Transaction History: tenure, credit score, balance, number of products, estimated salary, etc.,
- Customer behaviour: IsActiveMember, HasCrCard, etc.,

Depending on whether the client has closed his account (left the bank) or still continues to be a customer, the target variable is a binary value. This can be determined based on the customer's activity level or whether they have made any transactions within a certain period. The customer who leaves the bank is represented as 1 and the customer who continues to be with the bank is represented as 0. There are 10000 rows and 14 distinct columns in this dataset. The attributes Illustrated in the dataset can be summarized in Table II:

TABLE II. SUMMARY OF THE ATTRIBUTES

RowNumber:	Row Numbers from one to ten thousand
CustomerId:	It is a unique ID for the customer identification
Surname:	Customer Last Name
CreditScore:	Credit score of the customer
Geography:	location of the customers
Gender:	Male or Female
Age:	The age of the customer
Tenure:	Number of years the customer joined the bank
Balance:	Customer balance
NoOfProdcucts:	Number of products the customer is using
HasCrCard:	Binary flag, if the customer holds a credit card or not
IsActiveMember:	Binary flag, the customer is an active member with the bank or not
EstimatedSalary:	Estimated salary of the customer salary in Dollars
Exited:	Binary flag 1 for closing the account and 0 if the customer is retained

B. Data Preprocessing

Before a dataset is used to train a machine learning model, it must first go through several pre-processing steps. The objective of the pre-processing method is to convert unprocessed data into a form that may be used for modeling and analysis. In dataset pre-processing, the following methods are frequently used:

1) Data Cleaning

Dealing with missing or incorrect data values in the dataset is known as data cleaning. The first three columns of the dataset such as RowNumber, CustomerId, and Surname are the least important features which are self-labeled in the chosen dataset. These columns will be removed by the drop function for a better training process of the model.

2) Data Transformation

Data Transformation or Data Formatting demands converting the data into a format that is better suited for analysis. The format of the chosen dataset may not be appropriate. The dataset must be converted into a preferred format for the further model-building process. The columns such as Geography, Gender, and Surname have the same 'object' datatype. Balance and Estimated Salary are set to be in floating values. All other labels are kept in integer format.

3) Feature Selection

The feature selection was carried out by using variables that were present in the chosen dataset. Gender and Geography are the two categorical values present in the Churn_Modelling dataset. One hot encoding operation has to be done on the dataset as the first stage. To give categorical data variables to machine learning algorithms so they may use them to enhance predictions, one hot encoding method is used.

4) Feature Scaling

Feature scaling helps with regularization and feature comparison. It can improve the model performance and reduce computation time. Because of these reasons, it is very important to scale the feature values whenever Neural Network layers are trained specifically. The scaling process will be followed after splitting the dataset into training and testing sets. The most popular method is normalization, which is the process of rescaling characteristics to a range between 0 and 1. When the ANN model is trained without scaling its values then the value of weights present in the network won't converge quickly.

5) Data Splitting

The dataset is divided into three parts such as training, testing, and validation sets. The model will be trained with the training set, evaluated on the validation set, and finally, once it is ready to use, tested on the testing dataset. In order to split up the dataset into three similar sets by eliminating skewing, the total number of samples and the type of the model must be considered. There are 10000 data points found in the chosen dataset. In this use case, eighty percent of the data is retained for training, and twenty percent of the data is set for testing as well as for validation set.

C. Model Selection

Based on the literature review, the selected model is Artificial Neural Network (ANN) using Deep Learning for further studies. ANNs are extremely effective at making predictions and can be utilized for dealing with problems that are complex in nature. Customer churn prediction literature has increasingly used ANN, which has been demonstrated to have strong predictive ability. Due to the many models and architectures available now, the process of building a model using ANN has become more complex and less comprehensible.

D. Model Evaluation

The evaluation process set gives the opportunity to evaluate a model with data that it has never seen before. This is intended to be an accurate representation of how well the model might function in real life.

The dataset used for building the prediction models is quite large in size. Due to this reason, there is a high chance of getting an unfair prediction model because of the imbalanced distribution of the training and testing data. Hence a 2-fold method is used in splitting the dataset into train and test data. Initially, the model will be fitted into the training data and then the performance of the trained model will be evaluated on the unseen test data. Together with the accuracy of the prediction model, other metrics such as precision, recall, and F1-score are also considered. The classification report will print statistics on prediction and recall. A confusion matrix will be considered for evaluating the model's performance and prediction rate. This process will be done depending on the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) present in the confusion matrix, Fig 7. Two graphs are plotted using four key-value pairs such as loss, accuracy, val_loss, and val_accuracy which will indicate the overall loss and accuracy of each epoch that appeared at the time of training and validation processes.

E. Model Optimization

The output which is obtained after the training process of the model can be improved by making certain changes in the neural network, i.e., by tuning hyperparameters. First, the number of epochs has to be increased by repeatedly training the model with the complete dataset. Since the weight of a neural network cannot be found using any analytical method, it has to be found by experimenting with the model. Additionally, if the activation functions of the hidden layers are set to 'ReLu', then the model gives a better result compared to other activation functions. By implementing the concept of a validation split the accuracy level can be upgraded. This is considered one of the best techniques to validate the performance of a model. The validation split is done by subtracting the 20-percentage data from the training set. Along with the training process over the training dataset, the validation set will test over the 20-percentage of the dataset to find how the result is obtained. Finally, the performance and accuracy rate will be exponentially increased if the number of layers is increased to a finite number. But all these considerations are based on some experiments that have to be done by applying different values and functions.

IV. RESULTS AND DISCUSSION

The evaluation of the model has been done using the following methods:

1) *Loss and Validation Loss curves*
2) *Accuracy and Validation Accuracy curves*
3) *Classification Report*
4) *Confusion Matrix*

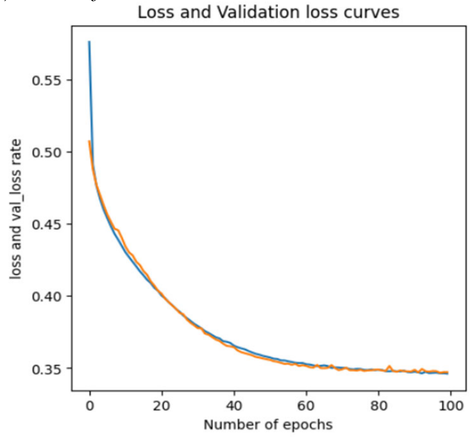

Fig 4. Loss and Validation Loss curves

Fig 4 Illustrates how the training and validation errors have been reduced during 100 epochs.

Fig 5 Illustrates how the training and validation accuracy has been increased during 100 epochs.

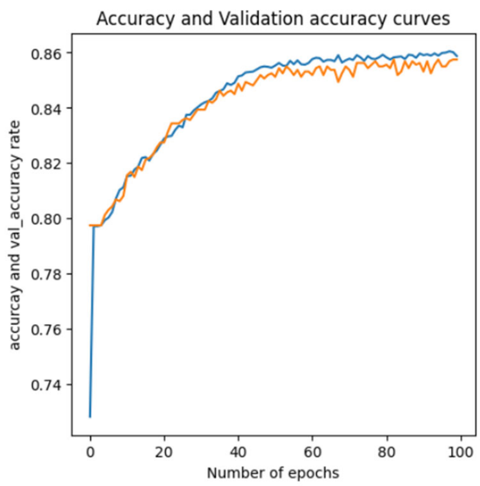

Fig 5. Accuracy and Validation Accuracy curves

A. *Classification Report*

The classification report provides an extensive breakdown of the most important metrics of the proposed ANN model. These metrics can be used to access a model's overall performance as well as to have a comparison of the performance of different models. The classification report Illustrated in Figure 6:

```
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      1585
           1       0.79      0.48      0.59       415

    accuracy                           0.86      2000
   macro avg       0.83      0.72      0.76      2000
weighted avg       0.86      0.86      0.85      2000
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Fig 6. Classification Report

B. *Confusion Matrix*

The resulting confusion matrix is Illustrated in Figure 7.

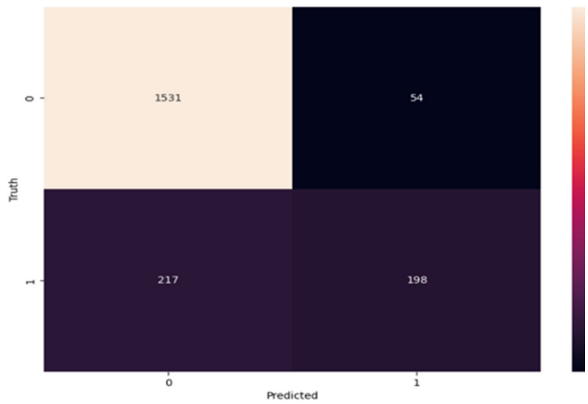

Fig 7. Confusion Matrix

- True Positives (TP): Based on the model, it shows how many times a customer is predicted to churn (1) and they did churn (1). [33]
- True Negatives (TN): This is represented as how many times the model predicted that the customer will not churn (0) and do not churn actually (0). [33]
- False Positives (FP): In the model, it represents the number of observations in which the customer was predicted to churn (1) but did not churn in real life (0). [33]
- False Negative (FN): It represents how many observations the model predicted would not occur (0) but in reality occurred (1). [33]

To analyze how well the ANN model performed, a comparison of the proposed ANN model has been carried out with the Logistic Regression model which is considered as the Traditional Statistical model for creating various prediction models. The summary of the results is illustrated below in Table III:

TABLE III. SUMMARY OF THE RESULTS

Prediction Model	Class 0				Class 1			
	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
ANN	86%	0.88	0.97	0.92	86%	0.79	0.48	0.59
LR	81%	0.83	0.96	0.89	81%	0.57	0.19	0.29

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN) \tag{1}$$

$$\text{Precision rate} = TP / (TP + FP) \tag{2}$$

$$\text{Recall} = TP / (TP + FN) \tag{3}$$

$$\text{F1- score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \tag{4}$$

From the results, it can be declared that the ANN model has achieved more accuracy and better performance than LR model.

V. DATA ANALYSIS (EDA)AND FINDINGS

These are the results of the Exploratory Data Analysis (EDA) which has been done using the main features of the dataset.

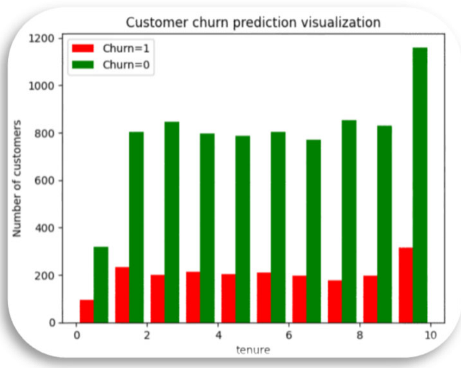

Fig 8. Number of Customers v/s Tenure

Figure 8 Illustrates how many customers are churning according to the number of years (tenure) that the customer has been a bank customer. When the number of customers is compared to tenure, it is shown that the majority of those with tenures of 10 are churning.

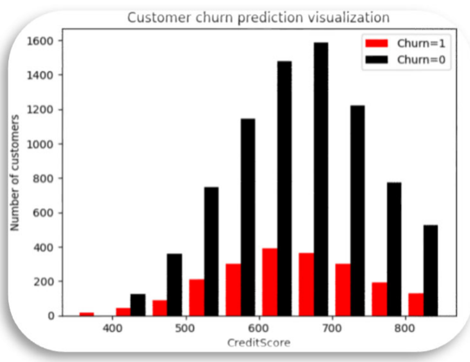

Fig 9. Number of Customers v/s Credit Score

Figure 9 illustrates a plot between the number of customers v/s their credit scores. When comparing Credit Scores with the total number of customers, it is clear that those with Credit Scores between 600 to 700 are churning.

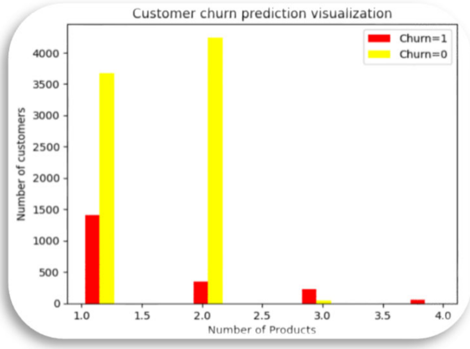

Fig 10. Number of Customers v/s Number of Products

According to the comparison between the number of products and the number of customers Illustrated in Figure 10, the customers with 1.0 are churning.

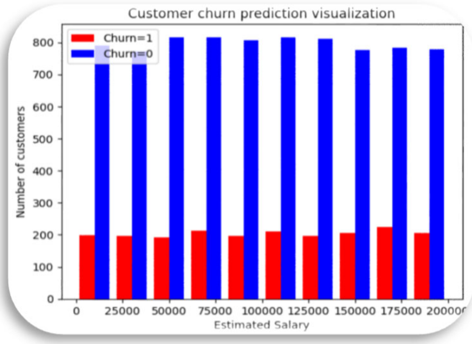

Fig 11. Number of Customers v/s Estimated Salary

Based on comparing estimated salary with the number of customers as Illustrated in Figure 11, it is found that customers who have an estimated salary between 175000 and 200000 are the most churned category.

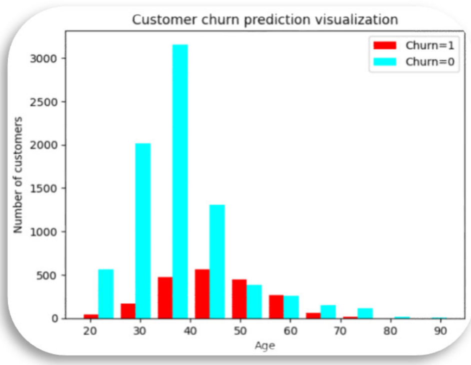

Fig 12. Number of Customers v/s Age

According to Figure 12, the customers who have the age of 50 are churning mostly from the bank.

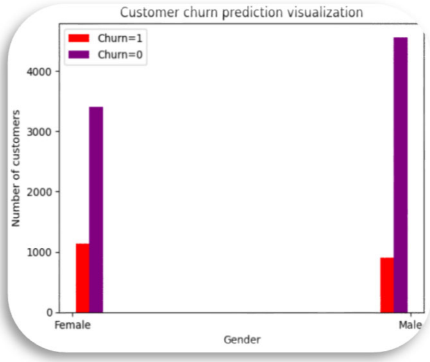

Fig 13. Number of Customers v/s Gender

By considering Figure 13, it is clear that Female customers are closing their accounts and leaving the bank, compared to the Male category in terms of churning.

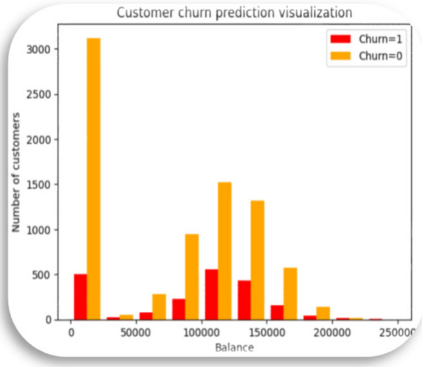

Fig 14. Number of Customers v/s Balance

Figure 14 illustrates a graph between the balance with the number of customers, those who have the minimum account balance i.e., zero balance are about to churn or be churned from the service. The graph depicts that the customers having a balance between 100000 to 150000 are churning from the bank service.

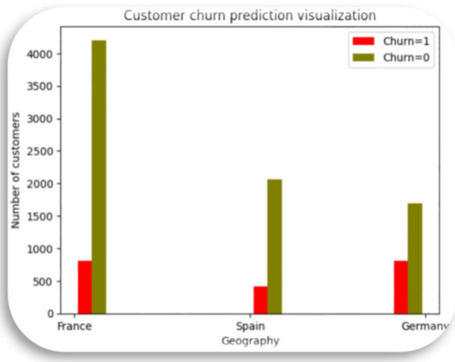

Fig 15. Number of Customers Geography

Comparing the number of customers with the geography, it is explicitly clear that mainly the customers who belong to France and Germany are churning more which is Illustrated in Figure 15.

'No of Products' is the feature that has the most significance out of all the features considered. People are less likely to be churned if they have a greater variety of bank products, such as Internet and mobile banking, savings accounts and fixed deposits, credit cards, etc. Therefore, the bank must concentrate on customers who use a limited number of products.

More focus shall be given to the Female category since they are at the stage of churning compared to the Male category.

The bank has to give special attention to the data features such as Geography, Age, Tenure, Balance, Credit Score, and Estimated Salary. If the bank takes care of these factors, then some effective policies and preventive measures can be implemented for customer retention.

VI. CONCLUSION

The goal of this research was to create a reliable model for predicting customer attrition in the banking sector using artificial neural networks (ANNs). The main objective was to assist banks in proactively identifying customers who might leave and take necessary actions to keep them from churning. Using Exploratory Data Analysis techniques the most relevant variables for the prediction model were identified. The ANN model was eventually created, trained, and validated using a variety of performance metrics, including the parameters such as accuracy, precision, recall, and F1-score. According to the findings, the suggested ANN model had an accuracy rate of 86% in predicting customer attrition. The ANN model has performed well in comparison to the performance of the LR model. The research identifies the specific areas in which banks should concentrate to help retain customers. Even though the study did not cover a comprehensive comparative study of different Machine Learning models such as Random Forest (RF), Decision Trees (DT), KNN (K-Nearest Neighbor), and Support Vector Machines (SVM), it navigates new directions for further research. The study used a small and highly imbalanced dataset which has only 10000 data samples for the model development process. But in the real-world bank data will be very large compared to the chosen dataset. To improve the accuracy of the churn prediction model, future research can concentrate on investigating various machine learning techniques, such as ensemble models, deep learning, and hybrid models. A comparative study of the ANN model with other Machine Learning models can be considered. Advanced research will give more ideas regarding how the dataset is trained in different Machine Learning algorithms and will be able to identify which model is the most effective prediction model

Additionally, future research can focus on improving the quality of the dataset by implementing advanced feature selection methods to enhance the performance of the model.

REFERENCES

[1] Cohen D., Gan C., Yong H.H. A and Choong E., (2006) "Customer Satisfaction: A Study of Bank Customer Retention in New Zealand." Lincoln University, Canterbury, ISBN: 1-877176-86-9, pp.7-8.

[2] Grigoreva S. (2023) "How to approach customer churn measurement in banking." Available at: https://uxpressia.com/blog/how-to-approach-customer-churn-measurement-in-banking#:~:text=Customer%20churn%20is%20when%20customers,other%20assets%20with%20the%20bank. Accessed on 7th July 2023.

[3] Khan Y., Shafiq S., Naeem A., Ahmed S., Safwan N., and Hussain S., (2019) 'Customers Churn Prediction using Artificial Neural Networks (ANN) in Telecom industry.' (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 10, No. 9, pp.142-152.K. Elissa, "Title of paper if known," unpublished.

[4] Hawkins J. and Mihaljek D., (2001) "The banking industry in the emerging market economies: competition, consolidation and systemic stability - an overview." BIS Papers No 4, pp.1-6.

[5] Hung, Chihli, and Chih-Fong Tsai. (2018) 'Market segmentation based on hierarchical self-organizing map for markets of multimedia on demand.' Expert systems with applications 34, no. 1: 780-787.

[6] Kaynak, E., and Kucukemiroglu, O. (1992). "Bank and Product Selection: Hong Kong." The International Journal of Bank Marketing, 10(1), pp. 3-17.

[7] Hull, L. (2002). "Foreign-owned Banks: Implications for New Zealand's Financial Stability." Discussion Paper Series, DP2002/05.

[8] de Lima Lemos, R.A., Silva, T.C. & Tabak, B.M. (2022) "Propension to customer churn in a financial institution: a machine learning approach." *Neural Comput & Applic* **34**, 11751–11768. https://doi.org/10.1007/s00521-022-07067-x

[9] Baltusevicius G., (2021) "The Importance of Churn Prediction." Available at: https://whatagraph.com/blog/articles/churn-prediction/#toc_4. Accessed on 26th March 2023.

[10] Buckinx, W., & Van den Poel, D. (2005). "Customer base analysis: partial defection of behaviourally loyal clients in a non-contractual FMCG retail setting." European Journal of Operational Research, 164(1), 252–268.

[11] Coussement, K., & Poel, D. V. d. (2008). "Churn prediction in subscription services: An application of support vector machines while comparing two parameter selection techniques." Expert Systems with Applications, 34, 313–327.

[12] Karahoca, A., & Karahoca, D. (2011) "GSM churn management by using fuzzy cmeans clustering and adaptive neuro fuzzy inference system." Expert Systems with Applications, 38(3), 1814–1822.

[13] Neslin, S. A., Gupta, S., Kamakura, W., Lu, J., & Mason, C. (2006) "Defection detection: Improving predictive accuracy of customer churn models." Journal of Marketing Research, 43(2), 204–211.

[14] X. Wang, K. Nguyen, and B. P. Nguyen, (2020) "Churn Prediction using Ensemble Learning." In Proceedings of the 4th International Conference on Machine Learning and Soft Computing, Association for Computing Machinery, New York, NY, USA, pp.56–60.

[15] Ajit, Bilal Z. (2016) "Predicting Customer Churn in Banking Industry using Neural Networks." Interdisciplinary Description of Complex Systems, 14(2), 116–124.

[16] Srivastava P. R., and Eachempati P., (2021) "Intelligent Employee Retention System for Attrition Rate Analysis and Churn Prediction: An Ensemble Machine Learning and Multi-Criteria Decision-Making Approach." Journal of Global Information Management 29(6):1-29. doi: 10.4018/JGIM.20211101.oa23

[17] Sharma A, Panigrahi PK (2011) "A neural network-based approach for predicting customer churn in cellular network services." Int J Comput Appl 27(11):26–31.

[18] Rosa, Nelson Belém da Costa. (2018) "Gauging and foreseeing customer churn in the banking industry: a neural network approach.", Nova IMS Information Management School, Lisboa, Portugal.

[19] El-Rayes, N., Fang, M., Smith, M., & Taylor, S. M. (2020). "Predicting employee attrition using tree-based models." The International Journal of Organizational Analysis, 28(6), 1273–1291. doi:10.1108/IJOA-10-2019-1903.

[20] Sisodia, D. S., Vishwakarma, S., & Pujahari, A. (2017) "Evaluation of machine learning models for employee churn prediction." In 2017 International Conference on Inventive Computing and Informatics (ICICI) (pp. 1016- 1020). IEEE. doi:10.1109/ICICI.2017.8365293.

[21] Guo-en X, Wei-dong J (2008) "Model of customer churn prediction on support vector machine." Syst Eng Theory Pract 28(1):71–77.

[22] Kamorudeen A. A., and Adesesan B. A., (2019) "Customer Churn Prediction in Financial Institution using Artificial Neural Network." https://doi.org/10.48550/arXiv.1912.11346.

[23] Meng Z., Hu Y., and Ancey C., (2020) "Using Data Driven Approach to Predict Waves Generated by Gravity Driven Mass Flows." doi: 10.3390/w12020600.

[24] Pattnaik S., (2023) Available at: https://youtu.be/99CcviQchd8. Accessed on 16th March 2023.

[25] Bre F., Gimenez J. M., and Fachinotti V. D., (2017). "Prediction of wind pressure coefficients on building surfaces using Artificial Neural Network." Available at: https://www.researchgate.net/publication/321259051_Prediction_of_wind_pressure_coefficients_on_building_surfaces_using_Artificial_Neural_Networks/figures?lo=1. Online Accessed on 16th March 2023.

[26] K. G. M. Karvana, S. Yazid, A. Syalim and P. Mursanto,(2019) "Customer Churn Analysis and Prediction Using Data Mining Models in Banking Industry." International Workshop on Big Data and Information Security (IWBIS), Bali, Indonesia, pp.33-38.

[27] K. Mishra and R. Rani (2017) "Churn prediction in telecommunication using machine learning." International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), Chennai, pp. 2252-2257.

[28] X. Wang, K. Nguyen, and B. P. Nguyen, (2020) "Churn Prediction using En- semble Learning." In Proceedings of the 4th International Conference on Machine Learning and Soft Computing, Association for Computing Machinery, New York, NY, USA, pp.56–60.

[29] B. He, Y. Shi, Q. Wan, and X. Zhao, (2014) "Prediction of customer attrition of commercial banks based on SVM model." Procedia Computer Science, vol. 31, pp. 423–430.

[30] Kim, H.-S., and Yoon, C.-H. (2004) "Determinants of subscriber churn and customer loyalty in the Korean mobile telephony market." Telecommunications Policy, vol. 28, no. 9-10, pp. 751-765.

[31] Buckinx, W., & Van den Poel, D. (2005). "Customer base analysis: partial defection of behaviourally loyal clients in a non-contractual FMCG retail setting." European Journal of Operational Research, 164(1),252–268.

[32] Satria W. A, Fitri I., Ningsih S. (2020). "Prediction of Customer Churn in the Banking Industry Using Artificial Neural Networks." Journal Mantik, Volume 4, No.1, pp.936-943.

[33] Mahanta, J. (2017) 'Introduction to Neural Networks, Advantages and Applications.' Available at: https://towardsdatascience.com. Online accessed on 7th July 2023.

[34] https://www.kaggle.com/datasets/rjmanoj/credit-card-customer-churn-prediction