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Customer Churn Prediction using Deep Learning

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Abstract : Churn studies have been used for years to achieve probability and to establish a sustainable customer-company relationship. Deep learning is one of the contemporary methods used in churn analysis due to its ability to process huge amounts of customer data.

A deep learning model is proposed to predict whether customers in the banking sector will churn in the future. The model developed is artificial neural network model, which are also frequently used in the churn prediction studies. You may be familiar with deep learning, a kind of machine learning that employs a multilayer architecture known as neural networks, from which the phrase neural network derives. In the form of a computer network, we create a network of artificial neurons that is similar to brain neurons. The artificial neural network is based on the collection nodes we will call the artificial neurons, which further model the neurons in a biological brain.

The results of the models were compared with accuracy classification tools, which are precision, recall etc. The results showed that the deep learning model achieved better classification and prediction success than other compared models.

***Index Terms* – Deep Learning, Churn, Artificial Neural Networks, Precision, Recall.**

I. INTRODUCTION

In today's dynamic and competitive landscape, the banking sector faces a pressing challenge: customer churn. Customer churn, the phenomenon where customers discontinue their relationship with a bank, poses significant financial and strategic implications for financial institutions worldwide. As customers have a myriad of options and are increasingly empowered to switch providers, banks must adopt proactive measures to retain their valuable clients.

The ability to predict and preempt customer churn has become paramount for banks striving to maintain market share, sustain profitability, and foster long-term customer relationships. Traditional methods of customer retention have proven insufficient in addressing the complexities of modern banking dynamics. However, advancements in deep learning offer a promising avenue for tackling this challenge head-on.

In recent years, Artificial Neural Networks (ANNs) have emerged as a potent tool for predictive analytics in various domains. Inspired by the human brain's neural networks, ANNs possess the capability to discern intricate patterns and relationships within vast and heterogeneous datasets. Leveraging this capacity, banks can harness ANNs to analyze historical customer data and forecast potential churn events with unprecedented accuracy and granularity.

This paper aims to explore the application of Artificial Neural Networks in predicting customer churn within the banking sector. By delving into the intricacies of ANN-based churn prediction models, we seek to offer insights into how banks can leverage deep learning techniques to optimize customer retention strategies.

II. LITERATURE REVIEW

Understanding how others have approached the problem of predicting when customers might leave a bank can provide valuable insights for our own research. Previous studies have used different methods, like statistical models and machine learning, to tackle this issue. However, we're particularly interested in exploring how Artificial Neural Networks (ANNs) have been used in this context.

Some studies have shown that ANNs can be really good at spotting complex patterns in large sets of data, like those found in banking records. These patterns could give us clues about which customers might be thinking about leaving. By looking at what other researchers have done with ANNs, we can get a sense of how effective they've been in predicting customer churn in the banking sector.

We'll take a close look at these studies to see how they've set up their ANN models, what kind of data they've used, and how well their predictions have worked out. By understanding what's been done before, we can build on that knowledge and make our own predictions even better. This part of our paper will help us see what's already been achieved and where there might be room for improvement in using ANNs for predicting customer churn in banking.

2.1 Artificial Neural Networks (ANNs)

Artificial Neural Networks, inspired by the structure and function of the human brain, are powerful machine learning algorithms capable of learning complex patterns and relationships from large volumes of data. In the context of customer churn prediction in the banking sector, ANNs offer a unique advantage by analyzing diverse datasets encompassing customer demographics, transaction history, service usage patterns, and other relevant factors. By leveraging this wealth of information, ANNs can discern subtle indicators and early warning signs of potential churn, enabling banks to intervene strategically and retain valuable customers.
Unlike traditional statistical methods, ANNs possess the ability to capture non-linear relationships, handle high-dimensional data, and adaptively learn from experience, making them well-suited for the complexities of churn prediction in dynamic banking environments.

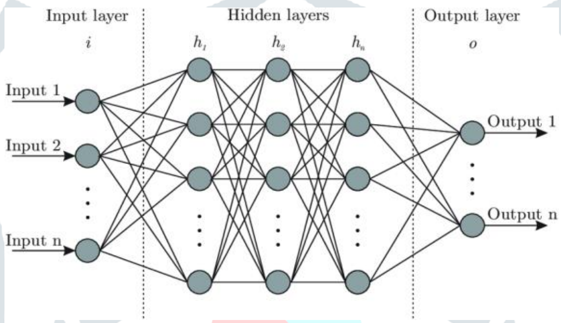

Figure 1. Artificial Neural Networks Architecture

III. Proposed Model and Methodology

The proposed model is Artificial Neural Networks using Deep Learning. ANNs are extremely effective at making predictions and can be utilized for dealing with problems that are complex in nature.

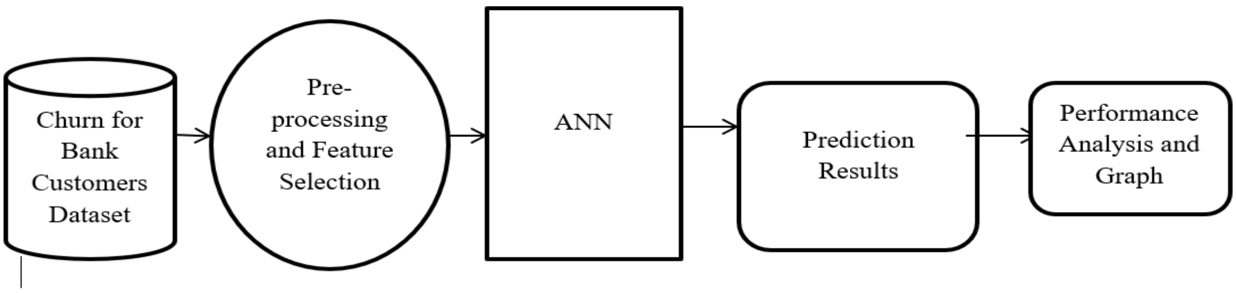

Figure 2. Proposed Model Architecture

3.1 Dataset

The dataset which we have taken is open source dataset named customer churn which is downloaded from the Kaggle. The dataset consists of 10000 individual data. There are 12 columns in the dataset, which are described below.

Table 1. List of Attributes in the Dataset

Row Number	Row numbers from one to ten thousand
Customer Id	Unique id for each customer
Surname	Name of the Customer
Credit Score	Score based on Transactions
Country	Customers location
Gender	Male or Female
age	Customers Age
Tenure	Number of years customer joined the bank
Balance	Customer Balance

Num Of Products	Products used by customers
Has Cr Card	Credit card available or not
Active Member	Customer is active member or not
Estimated Salary	Salary of the Customer
Exited	1 if customer is closing account or 0 if retaining

3.2 Preprocessing and Feature Selection

Before training an Artificial Neural Network (ANN) model for customer churn prediction in the banking sector, it is essential to preprocess the data and select relevant features to ensure optimal model performance. In the dataset there are some attributes which are not necessary for the prediction process. So, these attributes which are not useful in the prediction are removed for the training using preprocessing method. There attributes are Row number, Customer ID and Surname. These are least important features or attributes. So, these will be removed in data cleaning in the preprocessing.

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 algorithms so they may use them to enhance predictions, one hot encoding method is used.

3.3 ANN Model

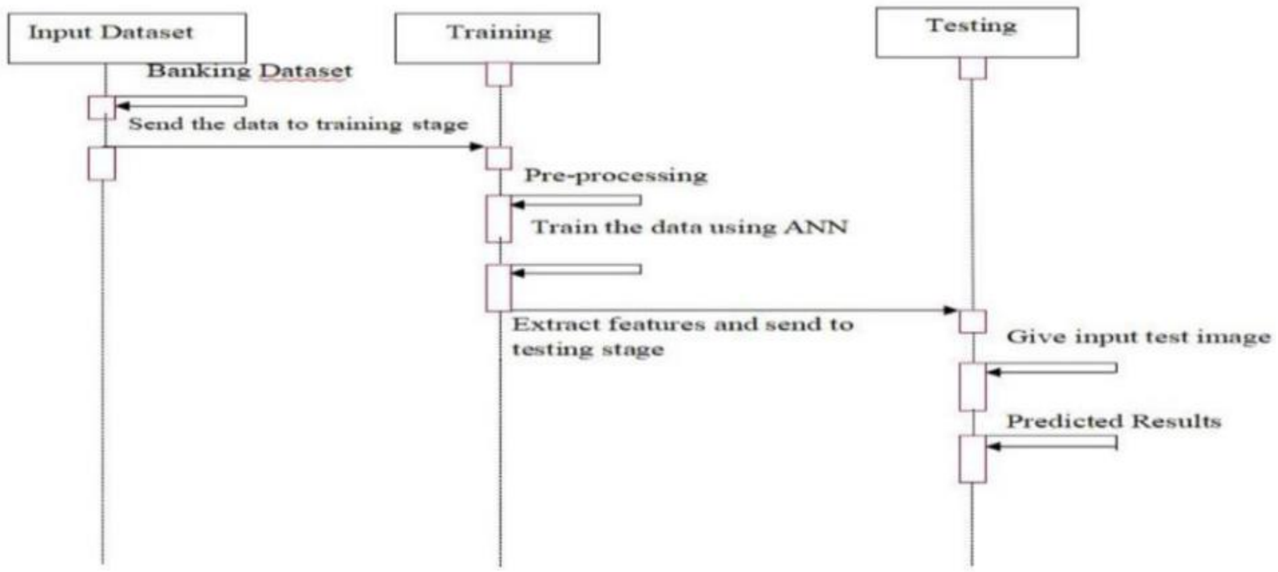

Figure 3. Working of the Prediction Model

After the Preprocessing and Feature Selection, the model is trained for the best prediction results. In the training process of the model, 80% of the dataset is used for the training and 20% of the dataset is used for testing the data. After the training process, the prediction results will be calculated. A web application is also developed for the customer churn prediction using the Flask software.

3.4 Software Requirements:

- Python version 3.8
- Libraries Required : Numpy, Pandas, Tensorflow, Flask, Matplotlib
- Execution Tools : Command prompt or VS Code Studio or Jupiter Software

IV. Results and Conclusion

4.1 Prediction Results

The model results in whether the customer will leave or will stay in the banking services. Model performance is measured with the confusion matrix outputs including accuracy, recall, precision.

4.2 Accuracy

After training and evaluating the model on the validation set, the accuracy of the model will be assessed on the test set. The accuracy on the test set will be an important metric for evaluating the model's performance. We got an accuracy of 86% on test set

4.3 Confusion Matrix

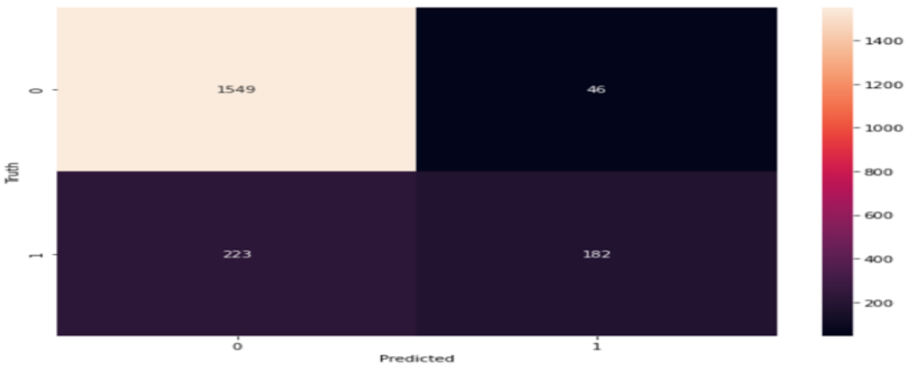

Figure 4. Confusion Matrix prediction results

The confusion matrix is structured as a grid with four quadrants, representing the four possible outcomes of a binary classification task (churned vs. non-churned customers). Below is the breakdown of each quadrant:

- True Positive (TP): This quadrant represents the instances where the model correctly predicts churned customers. In other words, the customer actually churned, and the model correctly identified them as such.
- False Positive (FP): This quadrant represents the instances where the model incorrectly predicts churned customers. In other words, the model predicted the customer to churn, but in reality, they did not.
- True Negative (TN): This quadrant represents the instances where the model correctly predicts non-churned customers. In other words, the customer did not churn, and the model correctly identified them as such.
- False Negative (FN): This quadrant represents the instances where the model incorrectly predicts non-churned customers. In other words, the model predicted the customer not to churn, but in reality, they did churn.

By analyzing the values in each quadrant of the confusion matrix, several performance metrics can be derived to assess the model's effectiveness, including:

- Precision: The proportion of true positives among all instances predicted as positive (TP / (TP + FP)). It measures the model's ability to avoid false positives.
- Recall: The proportion of true positives among all actual positive instances (TP / (TP + FN)). It measures the model's ability to capture all positive instances.

4.4 Precision and Recall

The precision and recall values of the prediction models are shown in the below table:

Table 2. Precision and Recall values

class	**Recall**	**Precision**
0	0.97	0.87
1	0.45	0.80

4.5 Conclusion

Customer churn prediction studies were conducted to reveal which customers are probably to leave the company. Several models and prediction techniques have been used. The deep learning methods, as one of the recent developments within the scope of artificial neural networks and are frequently used in image processing and image definition, can also be utilized in churn studies. In this study, a deep learning model in customer churn prediction was presented. The data was derived from a Banking dataset from Kaggle. Model performances were measured with the confusion matrix outputs including accuracy, recall, precision. According to these performance metrics, the Deep Learning model revealed higher accuracy of churn prediction compared to the other models. This helps Banks in retaining their customers and reducing the churn rate.

V. References

[1] C. Zhang, H. Li, G. Xu and X. Zhu, "Customer churn model based on complementarity measure and random forest," 2021 International Conference on Computer, Blockchain and Financial Development (CBFD), Nanjing, China, 2021, pp. 95-99, Doi: 10.1109/CBFD52659.2021.00026.

[2] A. Amin et al., ‘‘Customer churn prediction in the telecommunication sector using a rough set approach,’’ Neurocomputing, vol. 237, pp. 242–254, May 2017.

[3] A. Amin et al., ‘‘Cross-company customer churn prediction in telecommunication: A comparison of data transformation methods,’’ Int. J. Inf. Manage., vol. 46, pp. 304–319, Jun. 2019.

[4] Dingli, A., Marmara, V., Fournier, N.S.: Comparison of deep learning algorithms to predict customer churn within a local retail industry. International journal of machine learning and computing 7(5) (2017).

[5] Alboukaey, N., Joukhadar, A., Ghneim, N.: Dynamic behavior based churn prediction in mobile telecom. Expert Systems with Applications 162, 113779 (2020).

[6] L adyz_ynski, P., Z_ bikowski, K., Gawrysiak, P.: Direct marketing campaigns in retail banking with the use of deep learning and random forests. Expert Systems with Applications 134, 28{35 (2019).

[7] Martnez, A., Schmuck, C., Pereverzyev Jr, S., Pirker, C., Haltmeier, M.: A machine learning framework for customer purchase prediction in the non-contractual setting. European Journal of Operational Research 281(3), 588{596 (2020)

[8] Shah, M., Adiga, D., Bhat, S., Vyeth, V.: Prediction and causality analysis of churn using deep learning. Computer Science & Information Technology 9(13), 153{165 (2019).

[9] Migueis, V.L., Van den Poel, D., Camanho, A.S., e Cunha, J.F.: Modeling partial customer churn: On the value of first product-category purchase sequences. Expert systems with applications 39(12), 11250{11256 (2012).

[10] Baby, B., Dawod, Z., Sharif, S. and Elmedany, W. 2023. Customer Churn Prediction Model Using Artificial Neural Networks (ANN): A Case Study in Banking. 3ICT 2023: International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies. University of Bahrain, Bahrain 20 - 21 Nov 2023 IEEE.

[11] Liu, D.R., Shih, Y.Y.: Integrating ahp and data mining for product recommendation based on customer lifetime value Information & Management 42(3), 387{400 (2005)

[12] Liao, S.H., Chen, Y.J.: Mining customer knowledge for electronic catalog marketing. Expert Systems with Applications 27(4), 521{532 (2004)

[13] Chen, Y.L., Kuo, M.H., Wu, S.Y., Tang, K.: Discovering recency, frequency, and monetary (rfm) sequential patterns from customers' purchasing data. Electronic Commerce Research and Applications 8(5), 241{251 (2009)