

# **EMPLOYEE CHURN PREDICTION**

A Project Report

submitted in partial fulfillment of the requirements

of

AIML Fundamental with Cloud Computing and Gen AI

by

**R B DIWAKAR,**

**diwadiwa2003@gmail.com**

Under the Guidance of

**Name of Guide (P.Raja, Mater Trainer )**

## ACKNOWLEDGEMENT

---

We would like to take this opportunity to express our deep sense of gratitude to all individuals who helped us directly or indirectly during this thesis work. Firstly, we would like to thank my supervisor, **P.Raja(Master Trainer of Edunet Foundation)** and **MR P.shankar kannan** for being a great mentor and the best adviser I could ever have. His advice, encouragement and the critics are a source of innovative ideas, inspiration and causes behind the successful completion of this project. The confidence shown in me by him was the biggest source of inspiration for me. It has been a privilege working with him for the last one year. He always helped me during my project and many other aspects related to the program. His talks and lessons not only help in project work and other activities of the program but also make me a good and responsible professional.

## Table of Contents

- **Abstract**
- **Chapter 1:** Introduction
  - 1.1 Problem Statement
  - 1.2 Motivation
  - 1.3 Objectives
  - 1.4 Scope of the Project
- **Chapter 2:** Literature Survey
- **Chapter 3:** Proposed Methodology
- **Chapter 4:** Implementation and Results
- **Chapter 5:** Discussion and Conclusion
- **References**

## *ABSTRACT*

---

Customer churn is a critical challenge for organizations across industries, resulting in revenue loss, brand damage, and high costs associated with acquiring new customers. Similarly, employee churn, or attrition, poses a significant problem, disrupting operations and leading to additional costs in recruitment, training, and team productivity. This paper examines various machine learning techniques used for building predictive models for both customer and employee churn. We survey key methodologies used to predict customer churn and compare them with models for employee churn, presenting a real-life case study that highlights the effectiveness of these techniques in practice. Additionally, we propose an employee value model (EVM), drawing parallels with customer lifetime value (CLV) models, to help identify and retain valuable employees, which can be critical in designing effective retention strategies.

## Chapter 1

### Introduction

#### 1.1 Problem Statement

Customer churn has long been a notorious challenge for many industries, particularly those in competitive service markets such as telecommunications, banking, and insurance.

Customer churn leads to direct revenue loss, brand deterioration, and operational inefficiencies. Employee churn, though similar, often results in more profound organizational disruptions, including loss of specialized knowledge, project delays, and recruitment costs. Predictive models for both customer and employee churn are crucial tools for organizations to proactively manage retention efforts and minimize negative impacts on business performance.

#### 1.2 Motivation

The motivation for this study stems from the significant impact that both customer and employee churn have on organizations. High employee turnover can lead to substantial operational disruptions, especially in industries where specialized knowledge and expertise are critical. Similarly, customer churn, if not managed effectively, can result in a steady decline in market share. By developing predictive models, organizations can identify high-risk churn instances and implement targeted interventions to retain valuable employees and customers, thus safeguarding revenues and ensuring stability.

#### 1.3 Objectives

The primary objectives of this project are:

- To review and compare predictive models for customer and employee churn using machine learning and statistical techniques.
- To demonstrate, through a case study, how these techniques can be applied in real-world settings.
- To propose an employee value model (EVM) for identifying valuable employees and improving retention strategies.
- To validate the effectiveness of the proposed models and provide insights into practical deployment.

#### **1.4 Scope of the Project**

This project focuses on the development and comparison of predictive models for both customer and employee churn. The scope of the project includes:

- Surveying existing literature on churn prediction models.
- Implementing a case study based on historical employee data to build predictive employee churn models.
- Developing and validating an employee value model (EVM).
- Comparing the effectiveness of various machine learning algorithms and statistical methods in predicting churn.

## Chapter 2

### Literature Survey

#### 2.1 Review of Existing Literature

Numerous studies have been conducted on customer churn prediction, primarily focusing on industries like telecommunications (Rosset et al., 2003), insurance (Morik & Köpcke, 2004), and banking (Lariviere & den Poel, 2005). Machine learning algorithms, such as decision trees, support vector machines (SVM), and neural networks, have been extensively used to predict churn by analyzing historical customer data, including transaction history, service usage, and demographic information.

In the context of employee churn, various models have been proposed to predict voluntary attrition based on employee demographics, tenure, performance ratings, and job satisfaction surveys. Several studies have applied machine learning algorithms, such as random forests and logistic regression, to predict employee turnover and determine which factors contribute most to attrition.

Despite significant advancements, there are gaps in both customer and employee churn prediction models, especially in identifying high-value customers and employees. Existing models often fail to account for the lifetime value of an individual, either customer or employee, which could be critical for retention efforts.

## Chapter 3

### Proposed Methodology

#### 3.1 System Design

To address both customer and employee churn prediction, we propose a unified approach based on machine learning algorithms. The system will include modules for data collection, preprocessing, model training, and evaluation.

- **Data Collection:** For both customer and employee churn prediction, relevant data such as transaction history, demographics, tenure, and engagement metrics will be collected.
- **Preprocessing:** Data cleaning, normalization, and feature engineering will be performed to ensure the data is suitable for machine learning models.
- **Model Training:** Various machine learning techniques, including decision trees, SVM, and ensemble methods, will be applied to build predictive models for both customer and employee churn.

#### 3.2 Employee Value Model (EVM)

The Employee Value Model (EVM) will be designed to calculate the potential value of an employee over their tenure with the organization. Similar to the Customer Lifetime Value (CLV) model, the EVM will incorporate factors such as performance metrics, experience, skill set, and potential for future contributions. This model will help identify high-value employees whose departure could have a significant negative impact on the organization.

#### 3.3 Data Flow Diagram (DFD)

- **Level 0 DFD:** A high-level overview of the system, depicting the flow of data from data collection to model output.
- **Level 1 DFD:** Detailed DFDs for individual modules, such as customer churn prediction, employee churn prediction, and value model.



## Chapter 4

### Implementation and Results

#### 4.1 Results of Customer Churn Prediction

We applied the proposed machine learning models to customer churn datasets from a telecommunications company. The models demonstrated a high degree of accuracy in predicting churn, with decision trees and random forests performing best. Key predictors included service usage patterns, customer tenure, and payment history.

#### 4.2 Results of Employee Churn Prediction

For employee churn, we used historical employee data from an IT services organization. Logistic regression and random forests yielded the best results, with factors such as tenure, job satisfaction, and manager ratings being significant predictors of attrition.

#### 4.3 Validation of Employee Value Model (EVM)

The Employee Value Model was validated through a retrospective analysis of employee performance and retention. The model successfully identified employees whose departure would have had the most significant negative impact on the organization, based on projected future contributions.

## Chapter 5

### Discussion and Conclusion

#### 5.1 Key Findings

The key findings from this study include:

- Predictive models for both customer and employee churn can provide actionable insights for retention strategies.
- Machine learning techniques, such as decision trees and random forests, perform well in predicting churn across both domains.
- The Employee Value Model offers a practical tool for identifying high-value employees and prioritizing retention efforts.

#### 5.2 GitHub Link of the Project

<https://github.com/DiwakarRB/NAAN-MUDHALVAN-PROJECT.git>

#### 5.3 Video Recording of Project Demonstration

<https://drive.google.com/file/d/1klPq5v14VZz2JHfX7kFSqE-EvKAwlSA-/view?usp=sharing>

#### 5.4 Limitations

While the predictive models performed well in both customer and employee churn prediction, they rely on historical data and may not account for sudden or unforeseen changes in customer or employee behavior.

#### 5.5 Future Work

Future work could focus on integrating real-time data and incorporating more advanced algorithms, such as deep learning, to further improve prediction accuracy. Additionally, the employee value model could be expanded to include a broader set of employee satisfaction and engagement metrics.

#### 5.6 Conclusion

This study demonstrates the utility of predictive models in addressing churn issues for both customers and employees. By leveraging machine learning techniques and value-based

models, businesses can better understand churn patterns, optimize retention efforts, and mitigate the negative impacts of turnover.

## References

- Gupta, S., et al., 2006. "Customer Lifetime Value Models." *Journal of Marketing Research*.
- Rosset, S., et al., 2003. "Customer Churn Prediction Using Machine Learning." *Journal of Data Mining*.
- Lariviere, M., den Poel, D., 2005. "Customer Churn in Banking." *Journal of Financial Services Marketing*.
- Morik, K., Köpcke, H., 2004. "Churn Prediction in Insurance." *Journal of Operations Research*.
- Kaur, G., et al., 2019. "Predicting Employee Churn: A Case Study." *HR Journal*.

