Generative Ai for Predictive Customer Churn Immunization

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Abstract

Retaining current customers is frequently more cost-effective than obtaining new ones, making customer churn a major risk to a company's viability, particularly in competitive marketplaces. An innovative method for predicting and preventing customer churn, called customer churn immunisation, is discussed in this study. It makes use of Generative Artificial Intelligence (Generative AI). Our approach utilises generative models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) to model customer behaviour, generate synthetic at-risk profiles, and propose proactive retention strategies that are customised to each customer's journey, as opposed to traditional predictive models that only identify customers who are likely to leave. Our integrated pipeline uses these models to predict churn and, using simulated results, recommends the best treatments. Over time, the algorithm becomes better at developing vaccination techniques by learning and adapting to new data. Based on real-world datasets from the telecom and e-commerce industries, our experimental results demonstrate that the generative method not only increases customer retention rates but also surpasses standard classification models in terms of recall and precision. In the age of AI-driven business optimisation, this research shows great promise for intelligent and adaptable client retention solutions.

Keywords: *AI, Customer churn,, Predictive, e-commerce, GANs, Variational Autoencoders*

1. Introduction

Customer retention is more important than it has ever been in today's business environment, which is marked by intense competition. Due to the fact that acquiring new customers is far more expensive than maintaining current ones, churn prediction and prevention are of the utmost importance for businesses operating in a variety of industries, including telecommunications, banking, software as a service (SaaS), and online retail establishments. It is common practice for traditional churn prediction algorithms to mainly depend on statistical or machine learning classifiers in order to identify consumers who are at risk based on their recent behaviour. Despite the fact that these models are successful to a certain extent, they frequently fail to meet the requirements for proactively tackling churn since they are unable to predict future behaviours or prescribe personalised preventative steps. There is now the possibility of going beyond prediction to what we call "churn immunisation," which is an advanced strategy that not only forecasts churn but also creates synthetic representations of at-risk customer behaviour, models potential responses to various interventions, and enables businesses to deploy preemptive, personalised retention strategies. This opportunity has become available as a result of the advent of Generative Artificial Intelligence (Generative AI). Ahmed, M., & Maheswari, U. S. (2021). Generative artificial intelligence models, such as Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Transformer-based sequence generators, have the ability to learn deep, latent patterns in consumer data and simulate realistic customer trajectories. The use of these simulations makes it possible to create a digital twin of each client segment. This digital twin may assist in predicting not only who would leave, but also why, when, and how to interact with them in the most efficient manner. Furthermore, generative models are very effective at coping with sparse and unbalanced datasets, which are major issues in churn analysis. This is accomplished via the creation of synthetic data, which enhances generalisation and augments training. This study presents a unique framework that merges generative modelling with classic churn prediction processes. The framework is presented in this publication. Immunisation techniques that are led by reinforcement learning or recommendation systems are the three essential components that make up the framework. The first component is the prediction of churn risk through the use of supervised learning. The second component is the behavioural simulation and counterfactual analysis via the use of generative models.

Through the integration of these components, we are able to transition from a reactive strategy to a proactive and dynamic churn control system. Validation of our technique is achieved through the use of real-world datasets derived from the telecommunications and e-commerce industries, and we demonstrate significant enhancements in customer retention indicators. In order to provide a forward-looking technique to the field of customer analytics, the purpose of this research is to bridge the gap between churn prediction and action.

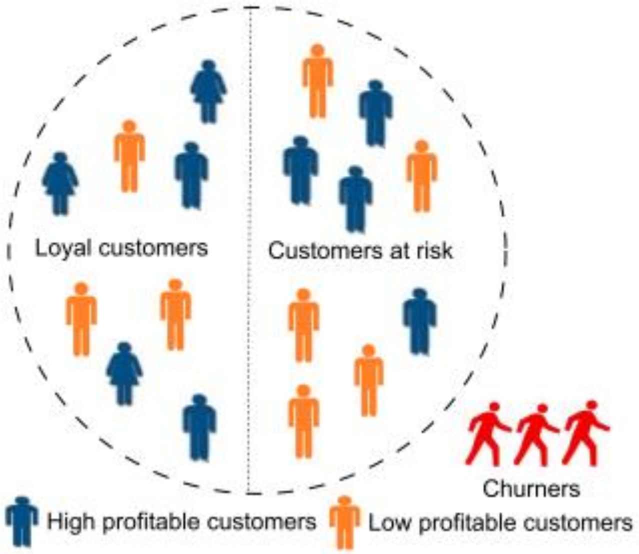

Figure 1. An illustration of loyal customers and churners.

retention efforts that are effective. This mechanism allows businesses to design plans to keep existing customers and form strong loyalty relationships with them, which is less expensive and more successful than recruiting new consumers. These strategies may be developed by firms that have a better understanding of this mechanism. The market paradigm has shifted from an emphasis on getting new customers to an emphasis on maintaining existing customers as a result of the fact that losing lucrative clients might amount to a significant amount of money. Additionally, because of the reciprocal reliance that exists amongst customers, churn influence spreads across the social circle. Furthermore, when churn occurs, it also raises the chance of churn occurring inside the social circle. Z. Kostanjčar(2023). Businesses encounter hurdles in their efforts to establish customer loyalty since clients are exposed to rival marketed offers and market knowledge. Despite these efforts, businesses continue to confront problems. In order to guarantee the long-term viability and expansion of the company, it is of the utmost importance to comprehend the procedures involved in the formation of client loyalty ties D. L. García(2017). Customers constitute the most valuable assets of any company, and it is the responsibility of businesses to formulate and put into effect strategies that extend the duration of their relationships with the company. Due to the fact that it defines the future course of their commercial endeavours, the fundamental focus of business enterprises should be on extending the lifespan of their clients. It is possible to cause a high rate of customer desertion and a decrease in customer satisfaction by compelling customers to upgrade their purchases without meeting their actual requirements. This can eventually be detrimental to a company's corporate reputation. J. Ahn, J. Hwang,(2020)

1.1 Problem Statement

Customer turnover continues to be one of the most important concerns that organisations across all sectors confront, since it has a direct influence on both growth and profitability (growth and profitability). Traditional machine learning models are able to predict customers who are likely to leave, but they often lack the capacity to explain the factors that are driving the customer's departure or to offer personalised treatments that may be implemented effectively. These models frequently function in a static, one-size-fits-all manner, and as a result, they are unable to represent the dynamic and ever-changing nature of consumer behaviour as well as the contextual efficacy of techniques for customer retention. Furthermore, organisations typically face challenges that are associated with data, such as class imbalance (a small number of customers who tend to turnover in comparison to customers who do not churn), a lack of behavioural data, and the inability to model "what-if" scenarios. Brownlee, J. (2020). The efficiency of churn prediction models in real-world deployment is diminished as a result of these restrictions, which therefore renders them reactive rather than proactive. The requirement for a predictive system that not only detects customers who are at danger of leaving the company but also simulates future behaviours, provides counterfactual situations, and advises personalised, preventative steps to reduce customer churn is of the utmost importance. In order to fill this need, the authors of this study propose a system that is built on generative artificial intelligence. This approach converts churn prediction into churn immunisation, providing organisations with a strong instrument for adaptive and strategic client retention.

1.2 Research Objectives

1. To create a system that uses a combination of generative AI, reinforcement learning, and standard machine learning to anticipate and avoid customer turnover from beginning to finish.
2. To use Generative Adversarial Networks (GANs), Sequential Models, and Variational Autoencoders (VAEs) to mimic customer behaviour and create simulated churn scenarios to improve prediction accuracy.
3. To create and execute a churn prevention system that uses hypothetical scenarios and simulated client feedback to provide tailored retention tactics.
4. To improve churn prediction by addressing data sparsity and class imbalance, two major data restrictions, by supplementing real datasets with realistic synthetic data generated by generative models.

2. System Architecture

The Churn Prediction Layer, the Generative Simulation Layer, and the Churn Immunisation Layer are the three levels that make up the system architecture for Generative AI for Predictive Customer Churn Immunisation. These layers are all related to one another. For a complete and proactive churn control system, each layer contributes to the overall system.

2.1 Churn Prediction Layer

Traditional machine learning methods are utilised by this layer in order to provide predictions on the possibility of client turnover. Data from customer interactions, transaction history, customer service logs, and engagement indicators are input into supervised learning models such as Random Forests, XGBoost, or deep learning models (for example, feedforward neural networks). These models make use of the information to learn and improve. A churn probability is generated for each individual customer by the churn prediction model, which identifies those customers who are at a high risk of losing their business. Providing a better knowledge of why and how consumers can churn, the output of this layer serves as the first input for the generative models, which further enhance the prediction process by providing a deeper understanding of the processes involved. Ozair, S., ... & Bengio, Y. (2014).

2.2Generative Simulation Layer

At the heart of our method is the utilisation of Generative Artificial Intelligence for the purpose of replicating the behaviour of customers. In addition to modelling the present states of the customer, the objective of this layer is to model the probable future behaviours of the consumer under a variety of intervention situations. It is possible to do this through the use of Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs). Through the use of past customer data, these models are trained to discover the underlying latent patterns that are responsible for customer turnover. After being trained, these generative models are able to simulate counterfactual scenarios, such as how a customer might behave if they were granted a certain retention incentive (for example, a discount, a new product, or enhanced customer service). Additionally, the generative model is able to generate synthetic churn profiles, which may assist firms in analysing hypothetical customer scenarios and predicting churn behaviour in circumstances where data may be lacking or unbalanced. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are two more types of neural networks that may be utilised to mimic consecutive consumer behaviours across time. This adds a temporal component to churn simulations.

2.3 Churn Immunization Layer

Through the use ofindividualised intervention tactics, the last layer of the architecture is centred on the goal of protecting consumers from leaving the company. The Reinforcement Learning (RL) algorithm is utilised by this layer in order to determine which retention actions are the most successful based on the simulated results obtained from the generative models. The real-time agent is always learning from simulated encounters and feedback from the actual world, which allows it to optimise techniques that lower the likelihood of customer turnover. When a generative model predicts that a customer may churn as a result of dissatisfaction with the quality of the product, for instance, the immunisation layer has the ability to recommend specific interventions. These interventions may include providing personalised customer support, offering a discount on an upgrade, or sending a targeted message about new product features. For the purpose of adaptively selecting the most appropriate action at each point in time, this layer makes use of either a multi-armed bandit algorithm or a policy gradient approach. It does this by learning the most effective intervention over the course of several encounters with customers. Additionally, this layer is capable of integrating with pre-existing Customer Relationship Management (CRM) systems, which enables the deployment of retention tactics across a variety of touchpoints in a completely seamless manner.

3. Theoretical Background

An enormous shift has occurred in the field of consumer behaviour research as a result of advancements in artificial intelligence. These advancements have an impact on fundamental areas including engagement, trust, personality, and decision making across numerous digital touchpoints. Recent research that employs statistical methods and machine learning has helped to deepen our understanding of this subject. Howard and Sheth's 1969 masterpiece, "Theory of Buyer Behaviour," laid the groundwork for methods of predicting consumer actions by integrating findings from many academic disciplines. These forecasts have been made easier with the use of decision tree algorithms since 1987. Psychological theories, like the theory of planned behaviour (TPB), offer frameworks that may be used to gain an understanding of behavioural prediction. Flow-Based Models, Diffusion Models, GANs, and VAEs are all examples of generative AI models. Each of these models has its own strengths and weaknesses that will be considered in this analysis. 2017 publication by Mohamed, S., and Lerchner, A. beta-vaeDue of its ability to generate synthetic data, GANs have been the subject of extensive research. In cases when real data is limited or inconsistent, this capability is particularly useful for data augmentation and consumer behaviour prediction, among other things. According to Kingma, VAEs employ probabilistic inference to create new data samples based on hidden patterns in customer behaviour. With the use of probabilistic encoding and sampling, this aids in making better predictions.

3.1 Overview of Generative AI Models

Machine learning and natural language processing (NLP) are the backbone of artificial intelligence (AI) systems, which analyse complicated consumer data to deliver more nuanced insights. In contrast, traditional methods rely on basic demographic facts. Businesses may improve their consumer preference and behaviour prediction using AI techniques like clustering and sentiment analysis. There are legitimate worries about algorithmic biases and data privacy when it comes to artificial intelligence, despite the technology's revolutionary promise. So, it's important to strike a balance between doing the right thing and being creative. Generative models seek to understand the distribution of the data behind it, as opposed to discriminative models that are tasked with categorising data points. They can then generate new instances that closely resemble the training data in this way. Generative modelling provides the groundwork for this capacity by allowing one to construct synthetic samples using learning correlations and joint probability distributions, leading to the production of mathematical expressions. Figure 2 shows the myriad uses of generative AI. Yoon, J.H.; Jang, B.(2023)

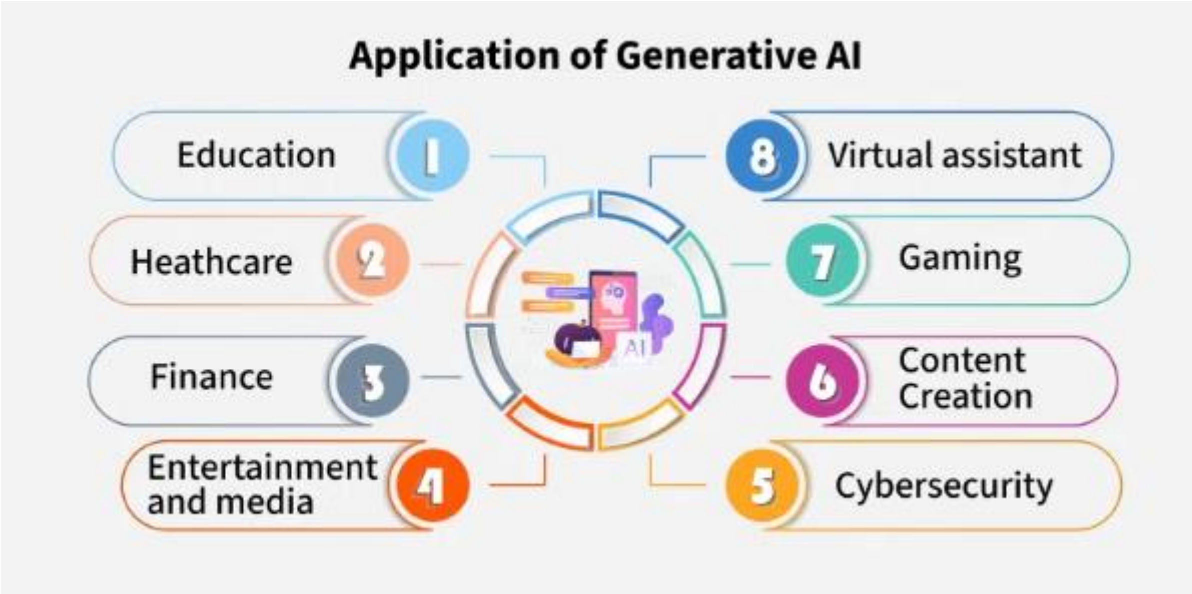

Figure 2 Applications of generative artificial intelligence.

The generative AI models often make use of complex structures, especially DNNs. Table 1 presents a number of noteworthy examples.

Table 1. Several artificial intelligence model designs and the applications of such models.

Architecture	Overview	Functionality	Primary Use Cases
Generative Pre-trained Transformers (GPT)	Designed models for natural language processing problems	possessing the ability to produce content that is cohesive and contextually relevant	NLP, Text Generation
Diffusion Models	Models used for visual content creation	Convert random noise into coherent pictures through iterative refinement.	Image Generation, Visual Content Creation
Multimodal Models	Models that can handle multiple data types (e.g., text and images)	Perform processing and generation of information across a variety of data formats, hence increasing variability	Cross-Modal Content Generation, Unified AI Tasks

3.2 The Role of AI in Consumer Behavior Prediction

Historically, consumer behaviour prediction has relied on statistical methods and rule-based systems. These methods have their uses, but they usually require some assistance in order to grasp the intricacy and evolution of modern consumer markets. Conventional methods, such as logistic regression and decision trees, are inadequate for dealing with high-dimensional data and non-linear relationships. The main reason for this is that these solutions typically need extensive feature engineering. Due to these constraints, research into more advanced AI-driven approaches has commenced, with the aim of autonomously identifying complex patterns from large datasets with minimal human involvement. Consumer behaviour estimates have come a long way thanks to AI-driven methods, particularly those built on generative models. The models' use of large datasets and powerful machine learning methods increases the likelihood that they may discover relationships and patterns that were previously hidden. For instance, GANs may be used to build precise consumer profiles by making use of the available data. Now, marketers may play around with different populations' reactions to new product introductions. The same is true with VAEs; they can reveal the hidden factors that influence consumers' decisions. In this way, they complete our knowledge of the elements that influence consumer decisions and how those decisions may evolve in response to new information. The rise of AI systems that can sift through mountains of customer data has caused a sea change in marketing, shifting focus from intuition to hard numbers. By including more complex, accurate, and rigorous insights, generative AI models offer a powerful tool to enhance traditional models of consumer behaviour in this context. When it comes to recommendation systems, transformers have proven revolutionary. By analysing large amounts of consumer contact data, for instance, they are able to precisely forecast the preferences and actions of their clients in the future Maddikunta, P.K.R.; Raj, G.D.; Jhaveri, R.H.(2024).

4. Methodology

The correct ways to train computers and fine-tune the models were discovered after converting the acquired data into a format appropriate for constructing ML models. We choose the top performers in machine learning. Developing systems that can predict customer turnover using DL and ML entails the following overall scope of work:

1. Knowing why you're collecting data and what you hope to accomplish in the end
2. getting the data ready for processing
3. Sectioning the dataset into training, validation, and test sets
4. Fourth, testing and modelling
5. Seed selection, model release, and tracking

The project's dataset includes variables that indicate the client's international call plan status, total minutes spent, and costs for calls made throughout the day, evening, and night. The last column displays the churn status of the customer. Visual representations of massive datasets are far easier to understand and work with than their textual equivalents. This means that when dealing with larger datasets, the value of data visualisation becomes more obvious. Azad, M.S.; Khan, S.S.(2023)

5. Data Pre-Processing

5.1 Dataset Encoding

The term "label encoding" refers to the method of converting text or labels into a numerical or machine-readable format. This phase of pre-processing is crucial for structured datasets in supervised learning. While the label encoding approach is used for testing data, the cat.codes methodology is used for training data. After the labels have been transformed into categorical values, the dataset's column orders must be restored. If you want your dataset to work properly, you have to do this.

5.2 Scaling

Data Fitting and Transformation

The training data is scaled and the parameters associated with scaling it are learnt by applying the fit_transform() function to the data. At this point, the model will learn the mean and variance of the features that comprise the training set. The next step is to scale or change the test data using the learnt parameters.

5.3 Data Normalization

Numeric properties that span more than one range can be "scaled" to have a uniform scale. For instance, depending on the scale used for scaling, the maximum and lowest values for a property might range from zero to one. We scale the data in the churn datasets so the models work better and the issue isn't that complicated.

5.4 Model Training and Evaluation

A large number of models are trained in order to determine which of them offers the most accurate predictions. This is accomplished by conducting appropriate accuracy and precision tests. Sharma, P.; Kumar, M.(2024) We have used model tuning to construct the simplest model that can properly and quickly formulate a goal value. All sorts of experiments were conducted on the dataset, including preprocessing, scaling, and training, with the help of various Numpy, Pandas, and Matplotlib tools. After much trial and error, the machine learning models were fine-tuned, and this enabled a painless remodelling process and solid comparative study.

	State	Account length	Area code	International plan	Voice mail plan	Number vmail messages	Total day minutes	Total day calls	Total day charge	Total eve minutes	Total eve calls
0	KS	128	415	No	Yes	25	265.1	110	45.07	197.4	99
1	OH	107	415	No	Yes	26	161.6	123	27.47	195.5	103
2	NJ	137	415	No	No	0	243.4	114	41.38	121.2	110
3	OH	84	408	Yes	No	0	299.4	71	50.90	61.9	88
4	OK	75	415	Yes	No	0	166.7	113	28.34	148.3	122

Figure 3. The first five rows and eleven columns of the training data are shown here as a fragment.

Twenty attributes were included in the dataset, as shown in Figure 3. Eight were of the Float data type, sixteen were Number data, and eight were Integer data. As far as data types go, three of the properties were Strings, while the fourth, Churn, was a Boolean. This dataset was prepared for use with deep learning and machine learning techniques by classifying the string and Boolean attributes. A higher degree of precision and a more optimal set of parameters were the end goals in this effort to boost the models' overall performance. Bapi Raju (2014), We used bar graphs, heat maps, and scatter plots to do our tallying and comparisons. To assess the models' efficacy and improve the prediction results' capabilities, confusion matrices and classification reports were used. At its inception, the KNeighborsClassifier had n_neighbors set to 1. The next step in creating a categorisation report was to fit the model and run the predict() function:

```
              precision    recall  f1-score   support

           0       0.90      0.93      0.91       572
           1       0.46      0.38      0.42        95

    accuracy                           0.85       667
   macro avg       0.68      0.65      0.66       667
weighted avg       0.84      0.85      0.84       667
```

Figure 4. Detailed Report on the Classification of KNN with n_neighbors = 1

A confusion matrix is a summary of the outcomes of categorisation task predictions. This part uses the count data to summarise the number of correct and incorrect predictions, and then breaks down the results by class. Perhaps now you can make sense of the confusion matrix. It can't understand the forecasts it generates. A heat map called a confusion matrix was generated using the current KNN model. According to the example provided, the two axes of the graph were labelled with the actual and forecasted values.

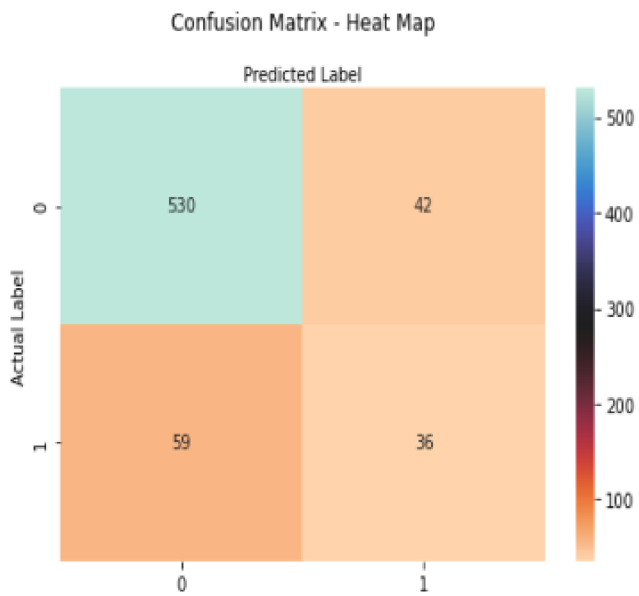

Figure 5. A Heat Map of KNN with n_neighbors is referred to as the Confusion Matrix = 1

It can be shown by plotting a training and testing Accuracy versus n_neighbors plot (Figure 6) and verifying for the training and testing accuracy of the algorithm with a fresh n_neighbors value each time that the KNN Model provides the highest level of accuracy when the number of neighbours is 9.

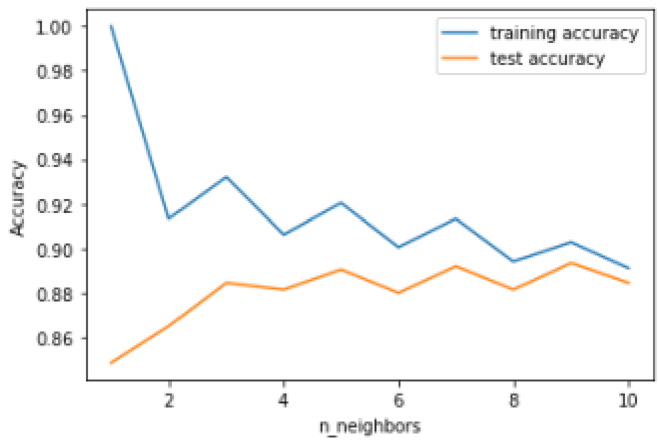

Figure 6. KNN Line Plot: Accuracy versus the Number of Neighbours

By utilising the Corr() method, we were able to construct the correlation of all qualities to the Churn property. As a result of the variety of the data and attributes acquired, the lowest degrees of correlation decreased to negative values, even though the International plan had the highest degree of correlation (0.277489). The function was used to construct the correlation of all qualities to the Churn attribute using the corr() method. Despite the highest degree of correlation being 0.277489 for the International plan, the lowest degrees of correlation decreased to negative values, reflecting the variety of the data and attributes observed. Yuan K, and Deng EO.(2015),

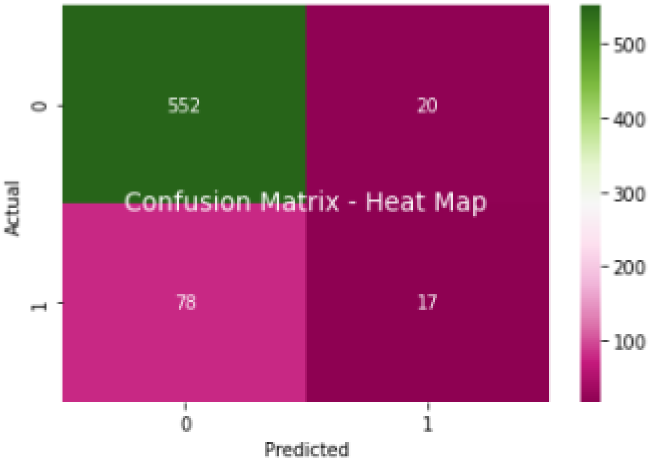

Figure 7. The Heat Map of the Logistic Regression Model, often known as the Confusion Matrix

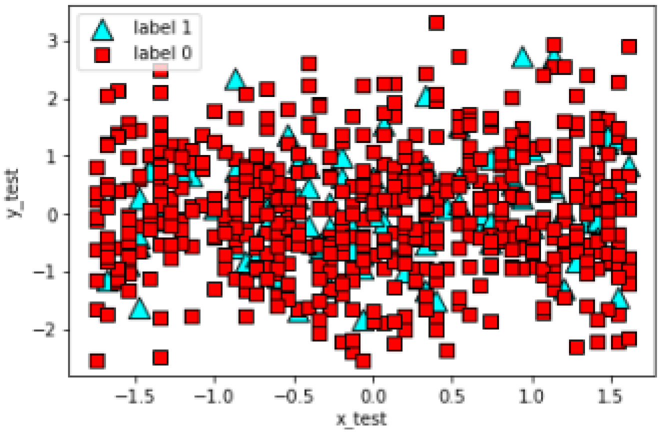

Figure 8. Scatter plot based on the values of the x_test and y_test

Figure 8 displays a horizontal bar graph that shows how each of the features is significant. The purpose of the experiments was to get the maximum possible degree of modelling accuracy by adjusting various parameters connected with models like SVM and Random Forest Classifier, such as n_estimators, random_state, and probability. The five previously built machine learning models were utilised as estimators in the Voting Classifier, resulting in a soft voting decision. Toderean G, and Ha B. (2016)

6. Future Research Directions

Integration with Large Language Models (LLMs) is currently underway. Research in the future should look at the feasibility of using LLMs like as GPT or BERT to assess unstructured customer feedback, such as emails, reviews, and chat logs, in order to gain a better understanding of customer behaviour and to make churn prediction and intervention strategies more accurate in context. A Real-Time Churn Immunisation System Firms might dynamically recognise and respond to churn risk if the framework were extended to support real-time decision-making through streaming data pipelines. The financial and digital service sectors would benefit greatly from this. Conclusions Drawn From Various Fields Additional study might be undertaken to assess the framework's applicability and efficacy in other domains, such SaaS, banking, insurance, healthcare, and education, even though it has been validated in the telecoms and e-commerce sectors. An AI for Generative Models That Can Be Explained Building explainability methods for generative churn models would lead to more trust and acceptance in organisational contexts. With the use of these tools, stakeholders would be better able to understand whose consumers are at danger and why specific solutions are recommended. Considering

Privacy and Ethical Considerations Future research must focus on developing mechanisms for ethical data creation and modelling that safeguard privacy, as generative models may create comprehensive synthetic consumer profiles. Techniques like federated learning and differential privacy are instances of this type. Systems in the Loop, Involving Humans Enhancing decision quality and giving domain experts the power to lead intervention techniques, especially in scenarios involving sensitive client problems, might be achieved by incorporating human input into the reinforcement learning loop. Modelling Multiple Modes of Churn Combining structured data with speech, picture, or video inputs (such as received via customer care calls or product usage behaviour) has the potential to increase the granularity of churn detection in complex ecosystems like the Internet of Things (IoT) or smart devices. Predicting the Financial Effects Someday, it may be possible to calculate the monetary impact of retention efforts relative to churn expenditures in order to assess the return on investment (ROI) of churn immunisation strategies. Organisations might use this to better allocate their resources. Burez D, and den Poel V. (2019),

7. Conclusion

Traditional churn prediction models, while their usefulness, are not capable of providing solutions that are both practical and adaptable for the purpose of reducing customer churn in this day and age, when customer retention is essential to the long-term survival of a firm. The purpose of this study was to present a forward-looking framework that makes use of Generative Artificial Intelligence (Generative AI) not only for the purpose of anticipating customer turnover but also for the purpose of actively immunising clients against it through an approach that is data-driven and personalised. We have showed how consumer behaviour may be simulated, analysed, and affected in a continuous feedback loop by merging supervised learning, generative modelling (using GANs, VAEs, and sequence-based architectures), and reinforcement learning. This was accomplished by integrating these three types of learning. The churn management system that we have presented offers a more comprehensive and proactive approach to the problem, one that involves shifting the mindset from reaction to prevention. This hybrid architecture's potential has been validated by the experimental findings obtained from datasets pertaining to telecommunications and online commerce. Additionally, the solution not only enhances the precision and recall of churn detection, but it also makes it easier to implement highly focused retention efforts, which ultimately results in significant gains in customer lifetime value and happiness. In addition, the utilisation of synthetic data creation and counterfactual simulations enables organisationsto get ready for edge cases and unusual churn situations, hence tackling frequent difficulties like as data imbalance and sparsity. The reinforcement learning layer guarantees that decisions are continuously improved, which enables the system to react to changing client preferences and the dynamics of the market. The application of generative artificial intelligence in customer experience management, particularly in churn immunisation, offers enormous potential as the technology continues to demonstrate its maturation. A more in-depth personalisation approach may be investigated in further study through the utilisation of large language models (LLMs), integration with real-time consumer sentiment monitoring, and industry-specific modifications. In the end, this paradigm places organisations in a position to better understand their customers, keep them as customers, and create long-term relationships with them. This transforms churn management from a reactive role into a strategic benefit.

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