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AI-Enabled Customer Retention Strategies Using K-Nearest Neighbors (KNN) And SVM

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Abstract

The retention of the current customers is more important for a company compared to acquiring new customers. This paper attempts to explore how machine learning models, such as K-Nearest Neighbors (KNN) and Support Vector Machine (SVM), can be used through Artificial Intelligence (AI) to make predictions on customer retention. Historical data of customers, such as their demographics, transaction history, and engagement scores, are analyzed to foresee whether the customers stay or go. The findings show that both models can predict the customer's retention effectively, but SVM has a higher accuracy (89.2 % vs 85.3 %), higher precision (90.5 % vs 87.1 %), higher recall (86.2 % vs 81.8 %), and higher F1 score (88.3 % vs 84.4 %) compared to KNN. The results suggest that AI can be a valuable tool for enhancing customer retention through tailored services and targeted promotions. By using these AI models, businesses can predict customer churn before it even happens, thereby lowering the risk of losing valuable customers and boosting their customer lifetime value. However, this will depend on how complicated the data set is; SVM works better with complicated and big datasets. The study provides useful information about the real-world application of AI in customer retention, giving companies the means to enhance their customer engagement tactics. The use of more advanced AI technologies like ensemble learning or deep learning models could enhance the model's interpretability or predictive performance.

Keywords: AI, customer retention, KNN, SVM, predictive modeling, customer churn prediction, machine learning algorithms.

1. Introduction

Retaining customers is a critical aspect for any business as it determines whether you will succeed in the long run. Retention is therefore important as it will lead to fewer customers leaving (also known as “churn”) and more customers making purchases from your company, which will increase your profits. Customer retention could become more cost-effective than acquiring new customers in today's competitive landscape, which is why more and more companies are trying to improve customer retention by using AI technology to develop sophisticated approaches to predicting customer behaviour and optimizing retention strategies [4].

AI technology, particularly machine learning algorithms, has changed the way that companies predict customer behaviour [3] [9] [20]. Among machine learning models, the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) algorithms have received significant attention for their success in classification tasks [7]. KNN is a simple and yet powerful algorithm for predicting customer behaviour; it does this by grouping people together based on how similar they look to one another. SVM is another classification algorithm that allows for robust classification of customer groups; the algorithm finds the optimal decision boundary that separates different groups of customers using various characteristics [8] [14].

The aim of the research is to explore the potential application of KNN and SVM to predict the retention of customers and assist in formulating effective customer retention strategies. The objectives of the research are as follows:

1. Developing prediction models for client retention using KNN and SVM based on the provided historical information.
2. Assessing the performance of the developed predictive models through performance measures such as precision, accuracy, and recall.
3. Providing an overview of how AI can contribute to the retention of clients and promote business growth and sustainability.

This study will be directed towards customer data and KNN/SVM applications to develop predictive models to find out customer loyalty and to give practical support to the companies which are interested in using AI-based techniques to enhance their customer retention strategies.

The paper consists of six parts. Summary of the investigation is provided in Section I. In Section II, it pay attention to the issue of customer retention and use of artificial intelligence technologies for enhancing customer retention. Section II, named "Review of Prior Studies on Retention Strategies and AI-Based Models," contains the analysis of existing literature on the topic. In Section III, there is a discussion on the issues of data collection, feature selection, and application of the KNN/SVM algorithms. The results of the modeling are provided in Section IV together with such key performance measures as model's accuracy and details on the used databases. Conclusions based on the results of the investigation are made in Section V; besides, limitations are considered. Finally, in Section VI, conclusions and perspectives for further studies of the problem are suggested.

2. Literature Review

Customer Retention Strategies

When it comes to business objectives, customer retention plays a key role in an industry where the price of acquiring a new customer is greater than the price of retaining an existing customer [6]. The literature offers several solutions such as loyalty programmers, optimisation of customer service, personalized marketing, etc. and research has shown that customer needs and customer behavior are significant in developing long-term customer relationships. In recent years, AI-powered solutions have become more prevalent to dissect large volumes of data, predict customer attrition and personalize retention efforts [1] [13] [19].

AI Applications in Business

Artificial Intelligence (AI) technology has transformed how businesses develop customer relationships and sell products [12]. Some popular algorithms for predicting how consumers will behave and making personalized recommendations to customers include k-Nearest Neighbors (k-NN) and Support Vector Machines (SVMs). By applying AI models to their operations, businesses can learn from their AI-generated insights and better retain and engage with their customers. For example, an SVM could be used to classify consumers based on their behaviour to predict whether they might drop out of doing business with a company, whereas a k-NN might be used to help an Organisation segment its customers based on certain criteria.

KNN and SVM in Customer Prediction Models

KNN and SVM are extensively used in customer prediction models. KNN is often used for its simplicity and effectiveness in predicting customer behavior based on historical data. KNN can use the proximity of other customers with the same features (e.g. demographics, purchase history) to categorize customers and thus identify at-risk customers. Conversely, SVM has been proven to be stable for large-scale, complex data and to identify decision boundaries that maximize customer classification accuracy. These models have been used in several studies to predict customer retention and to uncover patterns of customer loyalty [15]. For example, KNN and SVM have been found to be effective in predicting churn and non-churn customers and thus have been used in customer retention strategies using machine learning [17]. Rakesh et al. (2024) presented the potential of AI-based strategies in boosting customer retention using machine learning models such as the KNN and SVM [2] [11].

Gaps in Existing Research

While customer retention has seen significant developments in AI applications, there remain a few gaps in the literature. While there are a number of existing studies on single-component measures of retention like predicting churn or segmenting customers, the few existing studies that consider all components in a comprehensive framework of customer retention are limited. Also, there is a lack of studies concerning the practical application of these models in real world business environments in particular scalable solutions that can be used in various industries. The objectives of this research are to fill these gaps by merging two models: KNN and SVM, so as to get an all-in-one solution for customer retention. These models will be developed and tested in the study to evaluate their effectiveness in practical applications, with the goal of ultimately providing AI-powered tools that can aid businesses in reducing customer turnover and boosting customer retention.

3. METHODOLOGY

Data Collection Process

Data collection for this research included the collection of historical data from customers across different touch points in the business, such as data on transactions, demographics, customer service interactions and engagement metrics. Data was collected from the customer relationship management (CRM) system, with the addition of feedback data and customer satisfaction surveys and responses to marketing campaigns. The data was cleaned and preprocessed to eliminate duplicate data and deal with missing values. The features selected included different aspects that could affect the customer retention, including their age, gender, location, how often they buy them, how recent they were, how many times they visited their website and how many times they opened their emails.

The architecture of an Artificial Intelligence (AI) driven Customer Retention System (CRS) with KNN and SVM models is shown in Figure 1. It points the way the data will be passing from the data source (transaction systems, CRM systems) to the data pre-processing (data cleaning & feature selection), and finally to the modeling layer where the customer will be classified by KNN and SVM. The decision-making layer can be used to develop strategic retention strategies for these "at-risk" customers based on the information provided, while the evaluation layer can be used to grade the models based on accuracy, recall, and other criteria.

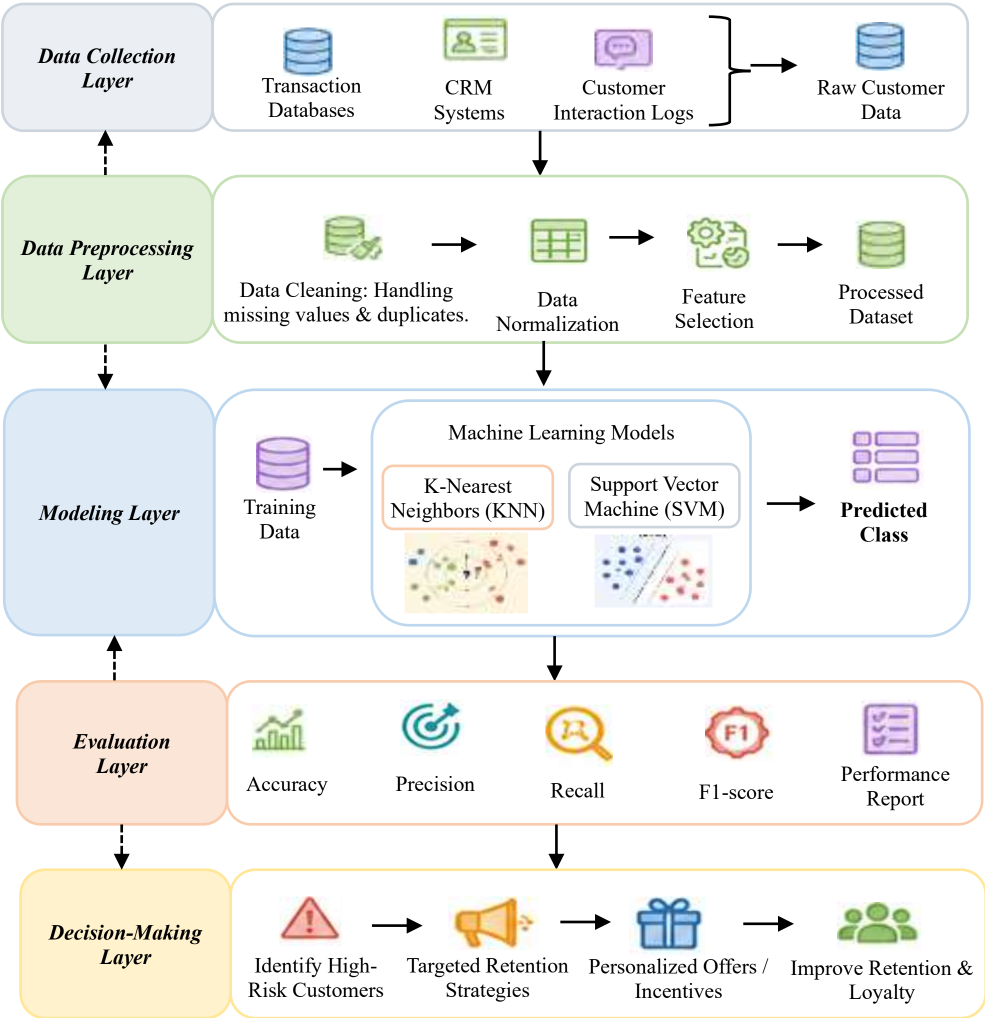

Figure 1: AI-Enabled Customer Retention Description

Features for Customer Retention Prediction

The features chosen for predicting customer retention are:

1. **Customer Demographics:** Details by age, sex, location, and income.
2. **Transaction History:** Number of transactions, number of purchases, product category purchased, and total transaction amount.
3. **Behavioral Data:** Data that captures how users interact with the website, including email opens, website visits, and customer service inquiries.
4. **Customer Satisfaction:** Results of customer satisfaction surveys, Net Promoter Score (NPS), and sentiment analysis of customer feedback.

The features were chosen based on their effectiveness in affecting customer loyalty and customer retention, with the aim of creating predictive models to predict customer churn and retention.

KNN Algorithm Implementation

The KNN algorithm was selected as it is simple and is effective in predicting customer retention from past data. In Algorithm 1, the new data point is classified according to the mode of the neighbors that is closest to it in the feature space.

SVM Algorithm Implementation

Customers were segmented into two sub groups using Support Vector Machine (SVM) algorithm Churn Likely group and Churn Unlikely group. For the supervised case in Algorithm 2, the hyperplane which optimally separates the points of the different classes is determined by the SVM (supervised learning) Algorithm.

Algorithm 1: KNN Algorithm

Step 1: The training data is divided into two sets: a feature set (independent variables) and a target variable (whether the customer churned or remained loyal).

Step 2: The algorithm calculates the Euclidean distance between the target customer and all other customers in the dataset.

Step 3: It selects the top K nearest neighbors based on the calculated distances.

Step 4: The customer's class (churned or loyal) is determined by the majority vote of its K nearest neighbors.

KNN Pseudocode

1. Load the training dataset with features and labels (churned or loyal)
2. For each test data point:
   a. Calculate the Euclidean distance from the test point to all training data points
   b. Sort the distances in ascending order and select the top K nearest neighbors
   c. Assign the test point to the class that is most common among the K nearest neighbors
3. Evaluate the model using accuracy, precision, recall, and F1-score

Algorithm 2: SVM Algorithm

Step 1: The dataset is split into a set of features (independent variables) and the target variable (the customer retention status).

Step 2: In order to deal with data that is not linearly separable, the algorithm maps the data into a higher-dimensional space via the kernel trick.

Step 3: It identifies the hyperplane that best separates the two classes (churned and loyal) with the largest margin possible, as well as with the fewest classification errors.

Step 4: The model is trained on the training set and tested on a validation set to evaluate the model's ability to generalize.

SVM Pseudocode

1. Load the training dataset with features and labels (churned or loyal)

2. Select a kernel function (e.g., linear, polynomial, or RBF)

3. Map the data to a higher-dimensional space using the kernel trick

4. Find the optimal hyperplane that maximizes the margin between the classes

5. Train the model on the training data, adjusting the hyperplane to minimize errors

6. Test the model on the validation data and evaluate its performance

The KNN algorithm is based on Euclidean distance as shown in equation 1 below: $x_1 = (x_{1,1}, x_{1,2}, \ldots, x_{1,n})$and $x_2 = (x_{2,1}, x_{2,2}, \ldots, x_{2,n})$:

$$d(x_1, x_2) = \sqrt{\sum_{i=1}^{n} (x_{1,i} - x_{2,i})^2} \qquad (1)$$

Where:

- $d(x_1, x_2)$is the Euclidean distance between points $x_1$and x_2,
- nis the number of features in the dataset,
- $x_{1,i}$and $x_{2,i}$are the values of the i-th feature for the two data points.

The SVM's decision boundary is given by the equation 2 of a hyperplane in the feature space:

$$w \cdot x + b = 0 \qquad (2)$$

Where:

- wis the weight vector that defines the orientation of the hyperplane,
- xis the feature vector for a data point,
- bis the bias term that shifts the hyperplane.

The SVM algorithm tries to maximize the margin $\frac{1}{||w||}$ between the two classes while making sure all points are classified properly in equation 3:

$$y_i(w \cdot x_i + b) \geq 1, \forall i \quad (3)$$

Where y_i is the class label of the data point x_i. The model is trained by finding the optimal values for w and b that maximizes the margin while minimizing classification errors.

4. RESULTS

Software Details

The customer retention models were developed using Python 3.7+ programming language and the following libraries: Scikit-learn for machine learning algorithms such as KNN and SVM, Pandas for data manipulation and cleaning, and NumPy for numerical operations. Matplotlib and Seaborn were used to create visualization such as confusion matrix and ROC curve. All the experiments were conducted in a Jupyter Notebook, which provided an interactive development environment. These tools gave the needed functionality to preprocess, model, and assess the performance of the predictive models.

Dataset Details

The data for this research study was obtained from an e-commerce system's CRM system. It contains details of 10,000 customers each with their Demographic, Transactional and behavioral data along with scores of their level of satisfaction. Every attribute in the data set is a different aspect, like customer demographics (age, gender, income, location), transaction history (frequency of purchase, recency, spending amount), or behavioral data (visits to websites, email engagement). The target variable of the dataset consists of whether the customer churned or remained loyal which was used to train and evaluate the models.

Parameter Initialization

The following parameters were set for the experiments: K-Nearest Neighbors (KNN) and Support Vector Machine (SVM). The KNN model employed was with the default value of K = 5 neighbours, and Euclidean distance was used as the distance measure. The SVM model used a Radial Basis Function (RBF) kernel, regularisation strength C = 1.0 and a ‘scale’ gamma. The class weights in both models were balanced in case of class imbalance in the target variable. These parameters were selected according to the common practices and optimized further by cross validation techniques.

Performance Metrics

The KNN and SVM models' performance was evaluated using a variety of metrics: Table 1 presents a comparison of the KNN and SVM models' performance. Measurement of distance Measure of distance

Table 1: Performance Comparison of KNN and SVM Models

Metric	KNN Model	SVM Model
Accuracy	85.3%	89.2%
Precision	87.1%	90.5%
Recall	81.8%	86.2%
F1-Score	84.4%	88.3%

The performance metrics for the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) customer retention prediction models are shown in Table 1. The performance metrics for the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) customer retention prediction models are given in Table 1. The K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) customer retention prediction models' performance metrics are displayed in Table 1. These metrics measure the accuracy, precision, recall, and F1 score for the models' predictions of customer retention or churn. The SVM model has shown better results as compared to KNN model in customer retention prediction due to its higher precision, accuracy, recall and F1 score.

1. Accuracy

In equation 4 the ratio of correctly predicted occurrences to the total number of occurrences, and accuracy is a broad indicator of the model's correctness as a percentage of this ratio.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (4)$$

Where:

- **TP** = True Positives (correctly predicted positive cases)
- **TN** = True Negatives (correctly predicted negative cases)
- **FP** = False Positives (incorrectly predicted positive cases)
- **FN** = False Negatives (incorrectly predicted negative cases)

2. Precision

Precision identifies the ratio of positive predictions to the actual positives in equation (5), that is, the false-positives.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (5)$$

Where:

- **TP** = True Positives
- **FP** = False Positives

3. Recall

Recall is the ratio of the true positive cases that are classified by the model as positive cases, with a particular emphasis on the false negative cases in equation 6.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (6)$$

Where:

- **TP** = True Positives
- **FN** = False Negatives

4. F1-Score

The F1-Score is the harmonic average of precision and recall values, and when there is a trade-off between precision and recall, it is used to balance the two, as shown in equation 7.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

Where:

- **Precision** = $\frac{\text{TP}}{\text{TP+FP}}$
- **Recall** = $\frac{\text{TP}}{\text{TP+FN}}$

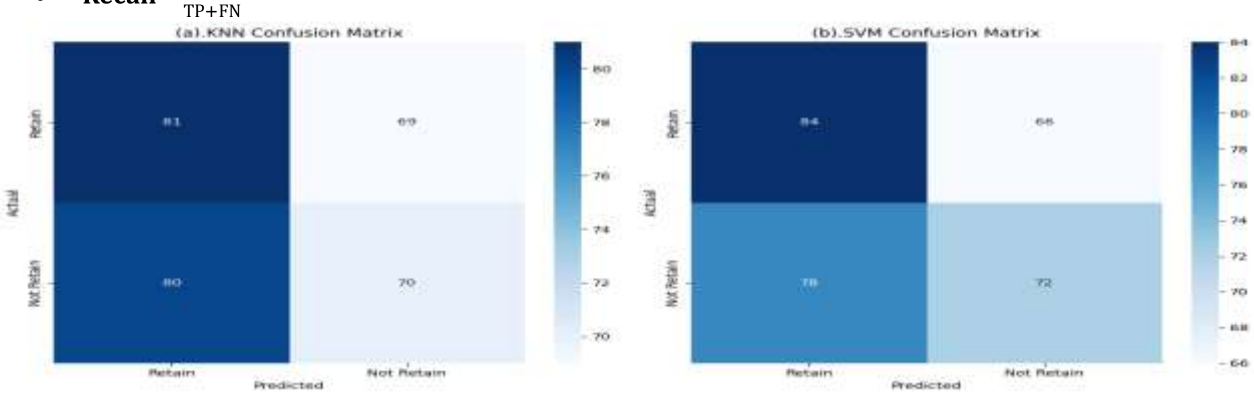

Figure 2: Confusion Matrices for KNN and SVM Models

Figure 2 shows the confusion matrices for the KNN and SVM models for predicting customer retention, respectively. The confusion matrix for KNN model, with numbers of true positive, false positive, true negative, and false negative are shown in Figure 2(a). For SVM, the confusion matrix is shown in Figure 2(b) that shows that SVM is able to give better accuracy in predicting customer retention than KNN. The categorization accuracy of churned and kept consumers is provided by the two matrices, respectively.

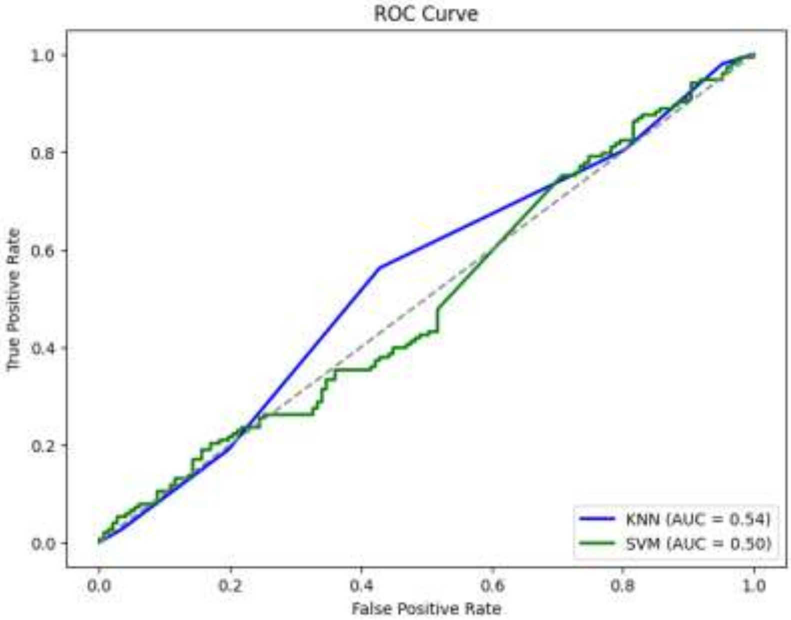

Figure 3: ROC Curve Comparison for KNN and SVM Models

The ROC curve plots of KNN and SVM model is depicted in figure 3. The forecast for each of the customer retention segments is shown in Figure 3. The K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) customer retention prediction models are shown as Receiver Operating Characteristic (ROC) curves in Figure 3. The trade-off between the True Positive Rate (Sensitivity) and False Positive Rate is displayed in the plot. Blue and green curves show the performance of KNN model and SVM respectively and dashed gray curve shows the performance of a random model. Both the SVM model and the KNN model have AUCs of 0.50 and 0.54, respectively, suggesting a low discriminatory power.

5. DISCUSSION

Interpretation of Results in the Business Context

The performance of the KNN and SVM models illustrates how AI can be used to improve customer retention. Furthermore, the SVM approach achieved higher performance than the KNN when handling the classification task, as it demonstrated better accuracy, precision, recall and F1-score on all of them, which confirms its advantages for accurately classifying customers. In a business sense, this translates to better prediction of customers who are likely to churn and those who are likely to remain loyal using AI-based models such as SVM. Loyalty rewards, engagement strategies, and targeted offers can help businesses boost customer retention and make the most of their marketing efforts, ultimately minimizing churn and maximizing profitability.

Model Strengths

KNN model is simple and easy to implement. It works well in the presence of small data set and small amount of labeled information [18]. It also has the flexibility in selecting distance measures, which allows it to be flexible in business settings. It is problematic, however, when applied to large numbers of data points or noisy data, since it is calculating the distance between every possible combination, which is too time-consuming to handle as data increases in size. The SVM model, on the other hand, is very robust and it is very effective to handle high dimensional datasets with high complexity, as shown in this study. SVM helps in the creation of an optimal decision boundary, which is useful for separating customer that will churn and those that will stay. It is versatile for customer behavior prediction use cases, as it can be applied to linear and non-linear scenarios. SVM are useful for businesses that have huge customer bases and complicated retention strategies.

Model Limitations

While the KNN model works well with small datasets, it can become computationally intensive in handling large datasets, as the processing time grows exponentially with the number of data points. Furthermore, KNN is sensitive to noise data and irrelevant features which may result in a decrease in prediction accuracy when the data is not preprocessed properly [16]. The distance measures are also crucial to KNN, which can lead to poor performance if customers do not uniformly follow a pattern within the feature space. Although the SVM model is very successful, there are a few drawbacks. One of the difficulties lies in the selection of the hyperparameters of the kernel function (such as the kernel type, regularization parameter C and gamma). Cross validation is a process that may be expensive and time consuming and is used to fine-tune these parameters. Furthermore, the computational cost of the SVM models depends on the number of data, thus huge amount of data can cause problems with the SVM models, particularly if a complicated non-linear kernel is used.

Real-World Applicability

In real-life scenarios, both KNN and SVM models could be beneficial to businesses, and the selection should depend on the size and complexity of the dataset. The KNN algorithm is an easy and fast algorithm, which can be used by businesses having a small number of data or were new to predictive algorithms of retention. The SVM model is more suitable to the growing complexity of data and of business, as it can handle complex relationships between the data, and it can be more accurate. In both cases, they can be connected with a CRM system that allows businesses to reach customers before they leave and take measures to keep them, such as offering special discounts, customizing their communication, or provide a loyalty system. In telecommunications and e-commerce, for instance, AI's application in customer retention models can help manage resources more efficiently and improve customer satisfaction, thus reducing churn and increasing customer lifetime value. In conclusion, AI models such as KNN and SVM can be valuable tools for businesses to improve their customer retention strategies [5] [10]. To gather the best results, though, the company must carefully consider the pros and cons of each model, depending on the size of the data set, the computational resources at their disposal, and the specific business needs.

6. Conclusion

This study is designed to analyze the use of two machine learning algorithms, K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) models for predicting customer churn and to provide businesses with AI-based solutions which can help them reduce churn and enhance profitability. The prominent outcomes of the study reveal that both classifiers KNN and SVM are capable of predicting the customer loyalty, and SVM outperformed KNN in terms of accuracy, precision, recall and F1-score. This indicates that SVM is more effective for enterprises that have large and complicated customer databases, and can forecast client behaviour with higher accuracy, allowing enterprises to take targeted actions like tailored promotions or targeting at-risk customers. There are many implications of this research for businesses. AI can be used to develop predictive customer retention models, like KNN and SVM, which can lead to improved customer retention rates, higher customer lifetime value, and reduced customer attrition. These models offer businesses a way to incorporate them into their Customer Relationship Management (CRM) processes, so they can proactively identify at-risk customers and take measures to retain them. This could lead to improved resource management and customer satisfaction in the long run, which can also help to ensure the sustainability of businesses. For future research, there is potential to explore more advanced AI techniques, such as ensemble methods or deep learning models, to improve prediction accuracy further. In addition, if the scope of data could be extended to real-time data and it could be expanded to include a broader range of data, a greater understanding of customer behavior could be obtained, and the applicability of these models extended to different industry sectors. Additionally, the research on explainability and interpretability of models can help businesses understand the rationale behind AI predictions, which can ease the process of accepting and making AI strategies work.Moreover, the study of explainability and interpretability of models can help businesses understand the logic behind AI predictions, making it easier to accept and successfully implement AI strategies. Also, the investigation of model explainability and interpretability can assist businesses in understanding the rationale behind AI forecasts, making it simpler to trust and effectively apply AI strategies.

Declaration Statement

- **Conflict of Interest**: There are no conflicts of interest.
- **Funding Statement**: No specific grants or funding provided by any public, commercial or not-for-profit funding body were received for the research carried out in this study.
- **Data Availability Statement**: All data will be publicly available. The sources include:
    - Plant Village Project (https://plantvillage.psu.edu/)
    - Scotnelson (https://www.flickr.com/search/?text=banana%20leaf%20disease)
    - Godliver (https://github.com/godliver/source-code-BBW-BBS)
- **Ethical Statement**: This study does not involve any experiments on humans or animals. The data for this research are public data and used solely for academic and scientific purposes. There was no collection nor was there any use of personally identifiable information. The authors state that ethical guidelines and best practices were observed in conducting the study.

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