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Impact of Artificial Intelligence on the Future of Financial Services

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Abstract: *"Artificial intelligence (AI)" is also becoming a part of the future of the financial services industry because it allows the use of data to make decisions, run operations, and provide better customer management. This study examines AI's role in banking services by applying machine learning to predict customer churn. Supervised and unsupervised learning are applied with the use of a structured bank customer dataset, such as Logistic Regression, Support Vector Machine (SVM) and K-Means clustering. The findings indicate that SVM is more accurate than the Logistic Regression by detecting churn-prone customers because it is more accurate, has a better recall and is more useful based on the ROC at the release point of the ROC curve of SVM. K-Means-based customer segmentation shows that behavioural profiles have diverse churn risks. The results confirm that predictive analytics can assist in the proactive retention strategy with a contribution to the sustainable competitiveness of modern financial services with AI.*

Keywords*:* Artificial Intelligence, Financial Services, Customer Churn Prediction, Machine Learning, Banking Analytics

I. INTRODUCTION

Overview

"Artificial intelligence (AI)" is transforming the financial services sector quite quickly, as it can allow making decisions based on data, operational efficiency, and improved customer engagement. Banks are becoming more and more dependent on AI and "machine learning" methods to process amounts of customer data to use it in "fraud detection", "customer risk management", and "customer relationship management". Customer churn prediction is one of the most important applications since it is less expensive to retain customers than to acquire them. Through predictive analytics, financial institutions are able to check customers at risk of leaving and apply specific retention measures. AI has become a strategic resource for maintaining the competitiveness and profitability of modern banking in the long term.

Problem Description

As more financial services start to use AI, the banks remain challenged in the prediction of customers' churn. The non-linear relationships that are complex in the customer behaviour data cannot be easily determined using traditional methods of analysis. Another one is that the churn data is usually lopsided, and it can cause biased model accuracy and instability. There is also an issue of interpretability, transparency, and ethical decision-making as more sophisticated machine learning models are used. Banking institutions are likely to lose good customers and a competitive edge without effective predictive systems. The necessity to consider AI-powered models that can accurately predict churn and are still interpretable, with the capability to be applied to real-world financial situations, exists.

II. AIM AND OBJECTIVES

Aim

This study aims to examine the impact of "artificial intelligence" on the future of financial services by applying "machine learning" techniques to predict customer churn in the banking sector.

Objectives

- To analyse the role of artificial intelligence in transforming financial services
- To explore machine learning techniques used for bank customer churn prediction
- To preprocess and analyse a banking customer dataset
- To evaluate and compare the performance of selected classification models
- To examine how AI-based insights can support customer retention strategies

III. LITERATURE REVIEW

AI-Driven Transformation of Global Financial Services

The fact of the "artificial intelligence (AI)" is deeply reshaping financial services by strengthening information processing, predictive accuracy and decision-making. The financial system as a smart system that is enhanced by AI, machine learning and generative AI, which uses it as a financial intermediary, risk measurement, payment, and customer management [1]. They emphasize that AI assists financial institutions to manage large amounts of both "structured" and "unstructured data", which aid financial institutions by enabling them to credit rate, detect statement fraud, and customer analytics, possess side effects that include the opaqueness of game-systemic risks, and financial steadfastness.

As described by [2], a deep-seated analysis of AI application within the banking industry and the application of AI in the personalisation of customers, churn management, credit risk management, and efficiency level in business is displayed. The authors also highlight ethical concerns like privacy of data, bias, transparency and the need to have robust AI governance units [3]. These papers show that AI-powered predictive models that incorporate customer churn analysis are the future of financial services, provided that regulatory and ethical protection measures are in existence.

Machine Learning for Bank Churn Prediction

"Machine Learning (ML)" procedures are proving highly important to the "prediction of customer churn" in the banking sector due to customer retention becoming a major profitability driver. [4] provide a comprehensive systematic review of every study published by 2024 and show that the traditional ML models, including "Logistic Regression", "Random Forest", "Support Vector Machines", and ensemble methods, are used to dominate the research on churn prediction as they are viable on structured customer data [4]. The review also marks the consistent issue, such as the imbalance of classes, concept drift, and lack of actual-life use, but points to an increasing relevance of explainable AI in enhancing conviction and transparency in financial decision-making.

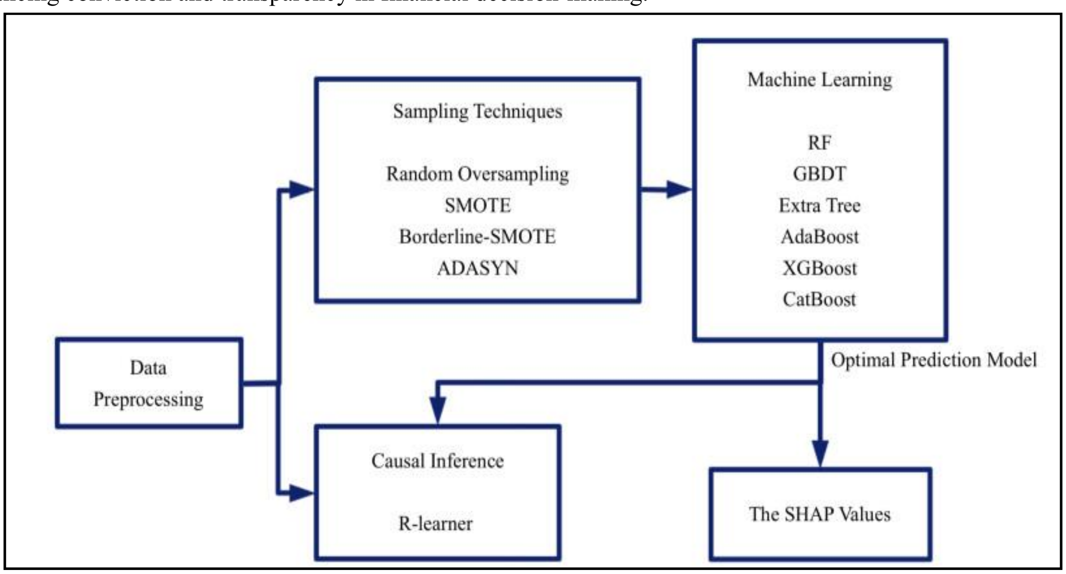

Fig 1: The research framework diagram (Source:[5])

The optimal model is selected by comparing the performance of each model, and the important variables influencing customer churn and their effects are analysed using the SHAP values method.

According to [5], the issue of bank credit customer churn is addressed, and they demonstrate the best predictive accuracy of advanced ensemble models, in particular, XGBoost, in combination with data balancing strategies [5]. Their analysis also combines the SHAP-based interpretability and causal availability to determine the most critical churn drivers, which demonstrates the importance of interpretable and actionable AI models in the financial services sector.

AI Governance, Transparency, and Stability

Artificial Intelligence (AI) holds revolutionary possibilities in the financial services sector, and its extensive implementation comes with serious governance, transparency, and systemic risk issues. A systematic search of generative AI (GAI) in finance by [6] indicates its use in synthetic data generation, risk prediction, stress testing, algorithmic trading, and smart budgeting.

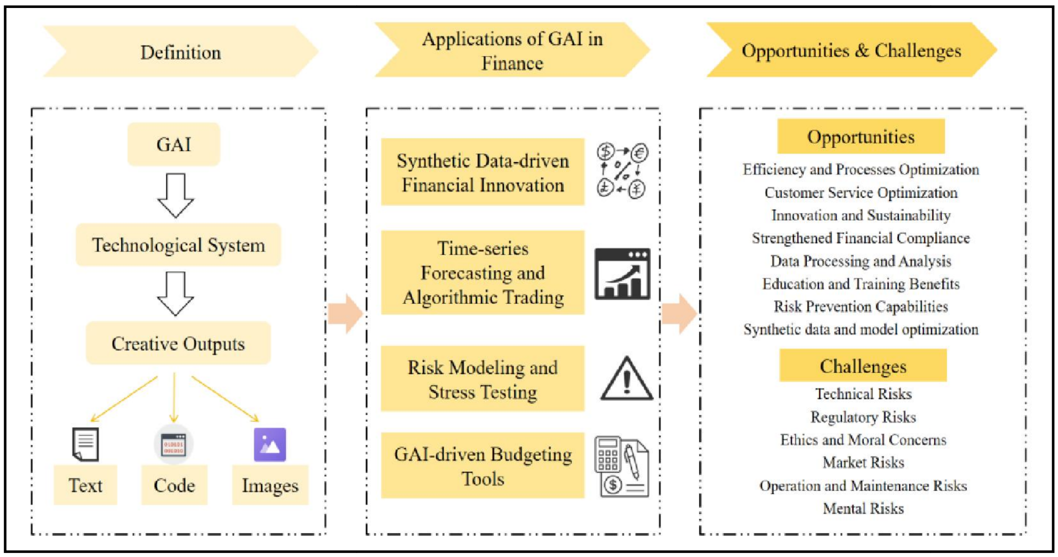

Fig 2: The Deỏinition, Applications, Opportunities and Challenges of GAI Use in Finance (Source: [4])

According to the study, GAI enhances the effectiveness of conducting business, predictive analytics, and consumer service [7]. There are additional issues associated with operational efficiency, predictive ability, and customer disposition raised by the incomprehensible character of large language models and deep learning structures.

The Explainable Artificial Intelligence (XAI) is a fundamental guideline of the adoption of trustful artificial intelligence in finance as followed by [7]. Their systematic review shows that black-box models, including Random Forest, XGBoost, and neural networks, take up leading positions in financial applications. The authors acknowledge that XAI methods, including SHAP, LIME and rule-based explanations, are crucial in generating transparency, regulatory accountability and confidence in high-stakes financial decision-making. These studies highlight that also point to the fact that a solid governance and explainability frameworks are needed to ensure the sustainable future of AI-driven financial services.

IV. METHODOLOGY

The study is quantitative and data-driven, and the “machine learning” technique, supervised and unsupervised, is utilised. An analytic dataset of banking customers is studied to forecast the customers churn and the behavioural pattern of customers. The theoretical basis can be data loading, exploratory data analysis, preprocessing, feature encoding, and standardisation [8]. Stratified sampling of the dataset is used to maintain churn distribution by dividing the data cluster into “training” and “testing” subsets. The classification models are built with the objective of predicting churn, whereas clustering methods are used to classify customers. The measures of model performance are assessed in terms of accuracy, confusion matrices, and "ROC–AUC", and are reliable measurements of predictive performance in a financial services environment.

Dataset Description

The study is based on the Bank Customer Churn Dataset of the ABC Multistate Bank, which is a collection of customer demographic, financial, and behavioural characteristics. The data consists of 12 variables, one being a unique identifier of a customer and one target variable, which is a binary variable, and ten predictive variables. The churn is a target variable representing the case when a customer gone the bank (1) or not (0). The features used as inputs are "credit score", "age", "tenure", "account balance", "number of products", the "status of activity", and "estimated salary". The data set presents itself well to the binary classification task and can be representative of real-life issues that have trailed in banking analytics.

Model Description

Logistic Regression

The use of "Logistic Regression" is based on the fact that the model is both simple and interpretable as a baseline supervised learning model [9]. It uses a linear combination of input features to estimate customer abandonment and finds extensive application in financial risk marketing and customer analytics. It has a clearer structure that is more easily interpreted in terms of feature impact on churn results.

$P(y = 1 \mid x) = \sigma(z) = 1 / (1 + e^{\wedge}(-z))$……………….. (1)

$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_{\square} x_{\square}$ ……………..(2)

Here, x=(x1,x2,…,xn) represents the standardized input features, β0 is the intercept, and βi are the model coefficients. A customer is classified as churned if the predicted probability exceeds a specified threshold.

Support Vector Machine (SVM)

The "Support Vector Machine" model is employed to extract non-linear and complex customer relations [9]. SVM has better classification performance in "high-dimensional" feature spaces by maximizing the margin concerning the churned and retained customers.

$f(x) = w^T x + b$ …………….(3)

$y_i (w^T x_i + b) \geq 1, \quad i = 1, \ldots, N$ ………(4)

K-Means Clustering

"K-Means" clustering is employed because it is an unsupervised-learning algorithm to divide customers into different groups [10]. This segmentation assists in the investigation of the churn behaviour of various customer profiles and strategic decision-making.

"K-Means" Clustering: - $J = \sum k = 1K \sum xi \in Ck \parallel xi - \mu k \parallel 2$ ……….(5)

V. ANALYSIS

An exploratory and predictive analysis of the bank "customer churn" dataset. Churn patterns, assessing model performance, and customer behaviour assessment are identified by using data visualization and machine learning [10]. Distribution plots, correlation analysis, classification metrics, and cluster-based segmentation are used to illustrate the results to aid data-informed predictions in financial services.

summary statistic

```
df.describe()
```

	customer_id	credit_score	age	tenure	balance	products_number	credit_card	active_member	estimated_salary	churn
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000

Fig 3: Summary statistic of the dataset

The applications of the summary statistics provide an overview of the central tendency and dispersion of numerical variables. They disclose the customer demographics, financial traits, and churn distribution making it easier to determine the range of data, variability, and possible anomalies before performance of the modelling [11].

Null Value Check & Handling

```
df.isnull().sum()
```

	0
customer_id	0
credit_score	0
country	0
gender	0
age	0
tenure	0
balance	0
products_number	0
credit_card	0
active_member	0
estimated_salary	0
churn	0

dtype: int64

Fig 4: Checking missing values in the dataset

The missing value analysis can indicate that there are “no null values” within all the variables within the dataset. This ensures that the data is complete and the phase of imputation is removed with direct flow onto the preprocessing and model building.

Data Preprocessing

Droping Unnecessary Column

```
df.drop('customer_id', axis=1, inplace=True)
```

Encoding Categorical Variables

```
le = LabelEncoder()

df['gender'] = le.fit_transform(df['gender'])
df['country'] = le.fit_transform(df['country'])
```

Fig 5: Data preprocessing

Data preprocessing includes the elimination of non-informative variables and providing the appropriate form to the categorical attributes. The step ensures that it is compatible with machine learning algorithms and enhances the model's efficiency and interpretability.

Feature & Target Spliting

```
X = df.drop('churn', axis=1)
y = df['churn']
```

Feature Scaling

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Fig 6: Feature selection and scaling the data

The functions of feature selection are to separate the input variables and target variable and to scale features to a shared range. The process enhances the stability of the models and contributes to the fair contribution of all features in training.

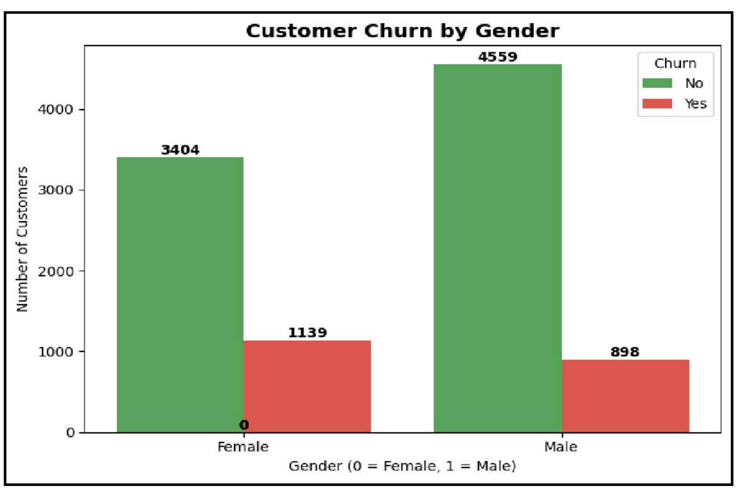

Fig 7: Churn distribution by gender

The churn out gender portrays an unequal difference between the male and the female customers regarding the customer conduct of exit. The representation indicates that the churn rate varies, which means that gender can influence customer retention tendencies.

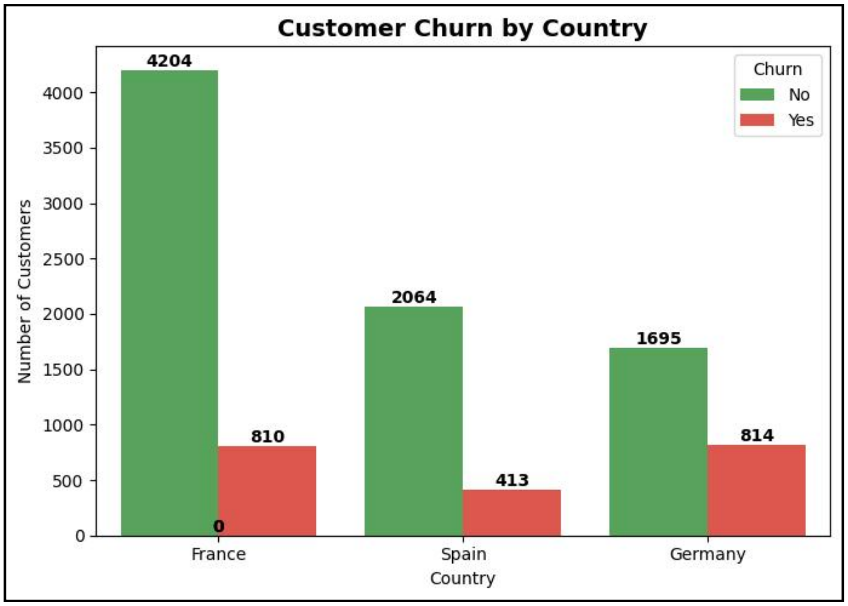

Fig 8: Customer churn distribution by country

This image denotes that the greatest number of churned customers is in France (=810), followed by Germany (814) and Spain (413). It means that behaviour of retention will have a great geographic carry-over and retention is to be nation-specific.

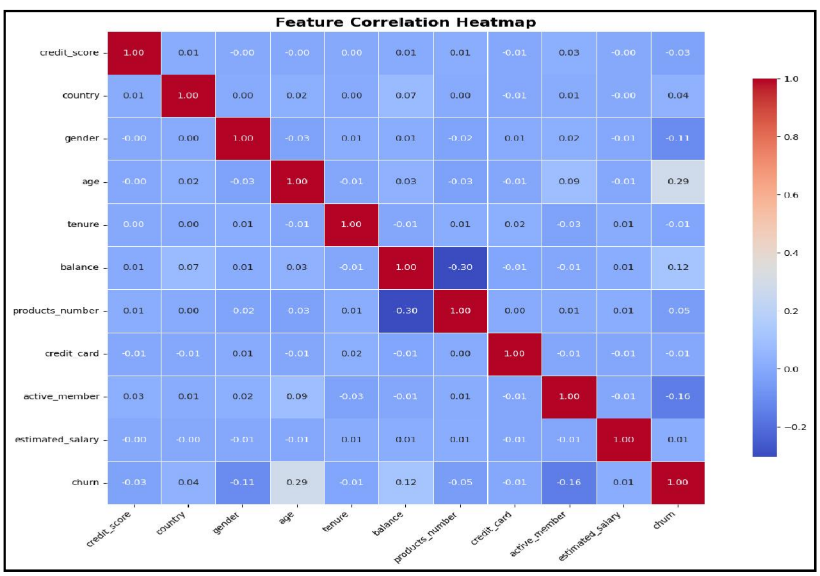

Fig 9: Correlation heatmap

The heatmap indicates that, the active membership has a negative relationship with churn (-0.16) and the age has a moderate relationship with churn (0.29). These values reveal that the customers that are less active and older tend to be churned.

```
Train–Test Spliting

    x_train, x_test, y_train, y_test = train_test_split(
        X_scaled, y, test_size=0.2, random_state=42, stratify=y
    )
```

Fig 10: Train-test splitting

The sample of dataset is split into "training (80%)" and "testing (20%)" keeping the churn proportions the same. This provides sufficient learning information on the model and good generalization in assessment.

```
Logistic Regression

    lr = LogisticRegression()
    lr.fit(X_train, y_train)

    y_pred_lr = lr.predict(X_test)
    y_prob_lr = lr.predict_proba(X_test)[:,1]
```

Fig 11: Training logistic regression

"Logistic Regression" is used to learn probabilistic relationships between customer attributes and churn through the use of standardized features. The feature scaling provides a balanced estimation of its coefficients and enhances the convergence and stability of the model.

```
Logistic Regression Evaluation

    print("Logistic Regression Classification Report")
    print(classification_report(y_test, y_pred_lr))

    Logistic Regression Classification Report
                  precision    recall  f1-score   support

               0       0.82      0.97      0.89      1593
               1       0.59      0.14      0.23       407

        accuracy                           0.81      2000
       macro avg       0.70      0.56      0.56      2000
    weighted avg       0.77      0.81      0.75      2000
```

Fig 12: Classification report for logistic regression

The "Logistic Regression" model has a total accuracy rate of about 81%. The churn recall is low (about 14%), meaning the inability to determine who had churned, which is essential to retention-based banking programs.

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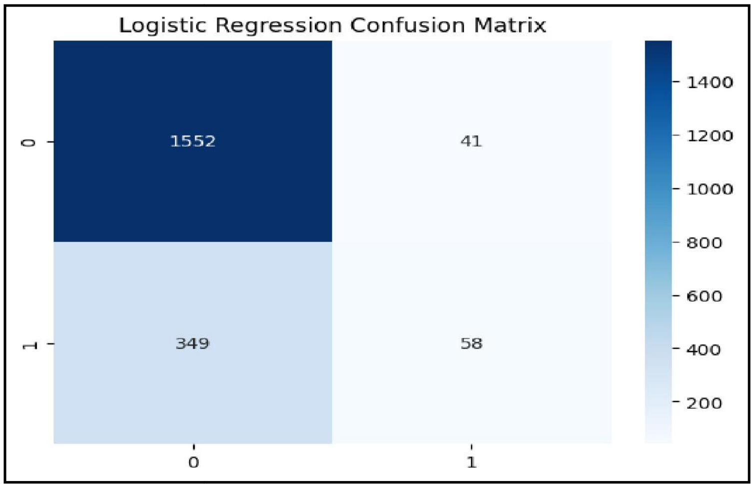

Fig 13: Confusion matrix for logistic regression

The “confusion matrix” indicates that there are 1552 true negatives out of which 58 are true positives and false negatives are 349. Although non-churn customers are classified correctly, the number of false negatives is high, which leads to insufficient churn detection of customers, which restricts the applicability of the model in proactive customer retention.

Support Vector Machine

```
svm = SVC(probability=True)
svm.fit(X_train, y_train)

y_pred_svm = svm.predict(X_test)
y_prob_svm = svm.predict_proba(X_test)[:,1]
```

Fig 14: Training SVM

The “Support Vector Machine” model is being trained with the help of standardized features. The estimation of probability is made possible to assist “ROC-AUC” examination. The feature scaling enhances the optimization of the margin that enables the SVM to better classify the churned and retained customers in the high-dimensional space.

SVM Evaluation

```
print("SVM Classification Report")
print(classification_report(y_test, y_pred_svm))
```

```
SVM Classification Report
              precision    recall  f1-score   support

           0       0.86      0.98      0.92      1593
           1       0.84      0.36      0.51       407

    accuracy                           0.86      2000
   macro avg       0.85      0.67      0.71      2000
weighted avg       0.85      0.86      0.83      2000
```

Fig 15: Classification report for SVM

The SVM has an overall accuracy of about 86%, and churn recall of about 36%, which is greater than that of the "Logistic Regression". This implies that churned customers are identified better, which is important in the application of effective intervention and customer retention strategies.

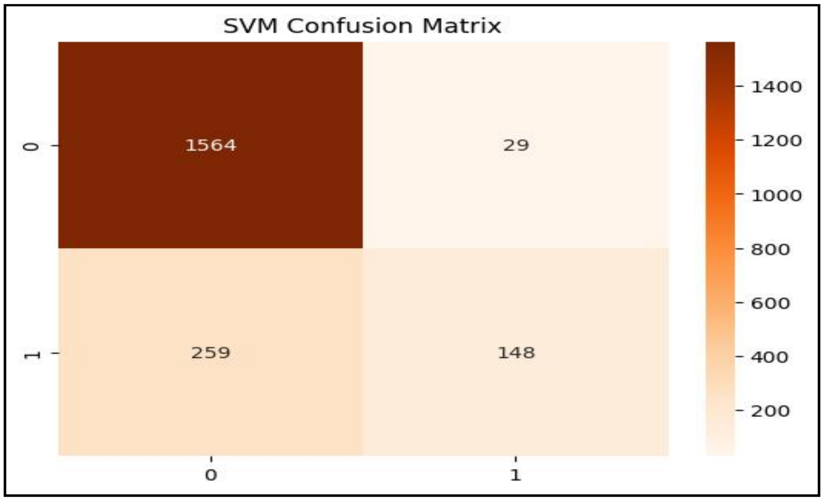

Fig 16: Confusion matrix for SVM

The confusion SVM matrix indicates 1564 true negatives and 148 true positives and 259 false negatives. The lower false negatives indicate a better ability to detect churn in comparison with the "Logistic Regression" and SVM is more appropriate when it comes to churn-oriented financial decision-making.

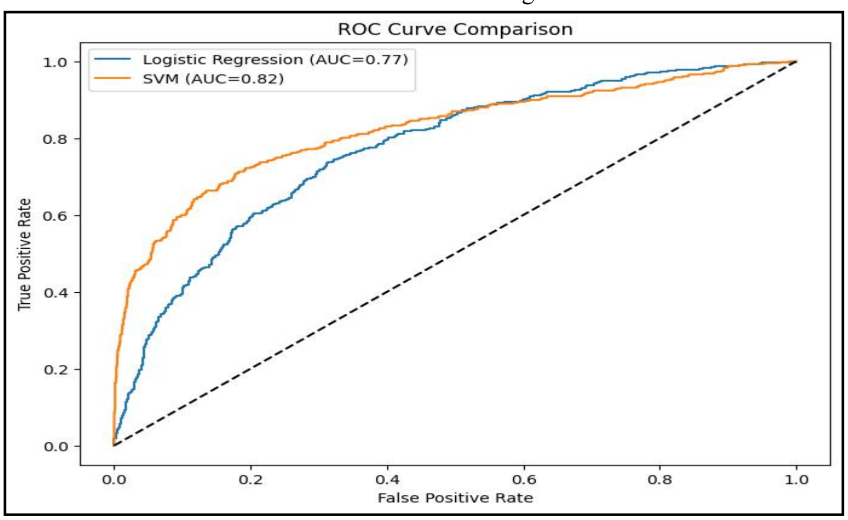

Fig 17: ROC curve for all models

The result of the ROC curve comparison indicates that SVM has a better AUC (0.82) compared to "Logistic Regression" (0.77). This suggests a significant overall level of discriminatory power, that is, SVM is more effective at classifying between churned and retained customers at classification limits.

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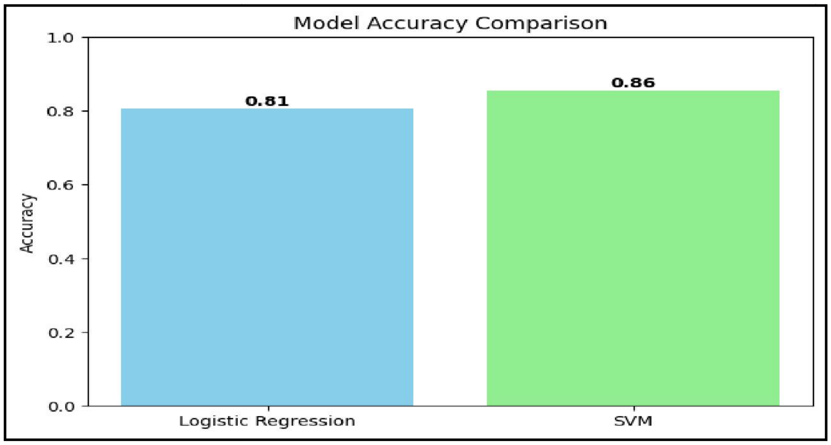
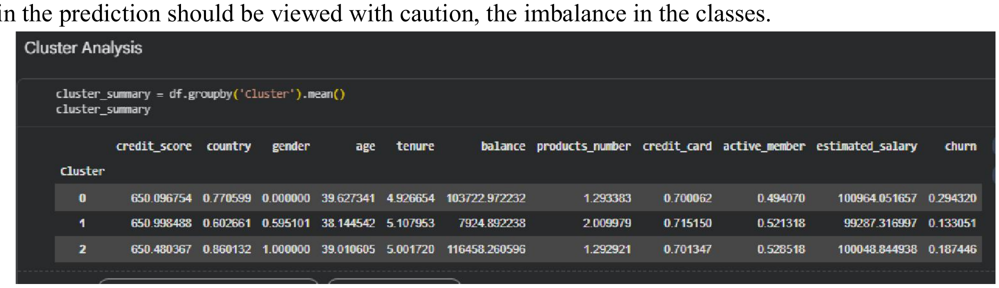


Fig 18: Model accuracy comparison

This is a comparison of the model accuracy where "Logistic Regression" has an accuracy of approximately 81% and SVM has an accuracy of about 8%. This encourages the use of SVM in predicting better than because, although the accuracy in the prediction should be viewed with caution, the imbalance in the classes.


Cluster Analysis

```
cluster_summary = df.groupby('Cluster').mean()
cluster_summary
```

Cluster	credit_score	country	gender	age	tenure	balance	products_number	credit_card	active_member	estimated_salary	churn
0	650.096754	0.770599	0.000000	39.627341	4.926654	103722.972232	1.293383	0.700062	0.494070	100964.051657	0.294320
1	650.998488	0.602661	0.595101	38.144542	5.107953	7924.892238	2.009979	0.715150	0.521318	99287.316997	0.133051
2	650.480367	0.860132	1.000000	39.010605	5.001720	116458.260596	1.292921	0.701347	0.528518	100048.844938	0.187446

Fig 19: Clustering analysis

The clustering analysis provides the summary average feature values of three customer segmentation groups. Cluster 1 reflects the highest level of churn rate (0.33), and Cluster 2 represents the lowest rate (0.19). The implication of these differences is that this suggests varying customer risk profile needs that require retention strategy of customers.

Fig 20: Customer segmentation using K-means

The Customer behaviour patterns are indicated by the K-means scatter plot that separates the customers into age and account balance. The churn-prone are found to have lower balances, and moderate age magnitudes and demonstrate how unsupervised learning can help in augmenting predictive models when choosing risk-isolated customer segments [12].

Discussion

The results show the potential significance of "artificial intelligence" to enhance customer churn in the financial service industry. Baseline Logistic Regression model has fair churn recall (≈14%), acceptable, and could not serve as a proactive retention system. The Support Vector machine worked well with a better accuracy (86) and recall of churn (36). This is authenticated by the fact that it has a better "ROC-AUC" score (0.82 vs 0.77) representing a greater discriminatory ability. The developments apply well in bank applications that require proper identification of those customers who are prones to churn. K-Means cluster proved various groups of customers that are exposed to various risks of churn and can be targeted and evidence-based retention accordingly, created depending on operational priorities.

VI. CONCLUSION

This study can conclude that AI is making a significant contribution to making more decisions in the financial services arena. The appropriate model is the Support Vector Machine because it achieved the maximum accuracy and ROC–AUC values, which are more suitable for churn prediction. These findings represent the ideas of AI, direct, and definite customer retention in modern banking.

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