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Predicting Customer Churn in Banking Sector

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Abstract: *Banking customer churn represents a high financial burden, since it is more expensive to attract new customers than to retain current ones. Based on our previous work [1], this paper presents a fair, scalable, real-time churn prediction framework that mitigates data quality issues, lack of model interpretability, and adherence to regulatory policies. We combine cutting- edge data sources, including customer interaction sentiment analysis and temporal patterns of transactions, with state-of-the-art machine learning models, including LSTM networks and fairness-aware Random Forests. Our suggested methodology attains an AUC-ROC score of 0.97, a precision improvement of 20% compared with our earlier hybrid model (AUC=0.95), and guarantees fairness with demographic parity metrics. Implemented through a cloud-based FastAPI pipeline, the system allows banks to implement focused retention strategies that lower churn rates by approximately 25%. The contribution of this work lies in data science as it presents a workable, ethical, and scalable approach to customer retention in banking with possible extensions into other industries such as telecom and retail*

Keywords: Customer Churn, Banking Sector, Machine Learning, Real-Time Prediction, Fairness-Aware Models, Deep Learning

I. INTRODUCTION

Customer churn, the behavior by which customers end their relationship with a bank, directly affects profitability, as customer retention costs 5-25 times that of acquiring new customers [2]. Our earlier work [1] constructed a hybrid churn prediction model based on logistic regression, Random Forest, and Support Vector Machines (SVM), which obtained an AUC-ROC value of 0.95 and accuracy of 0.98. Real-time prediction limitations, interpretability, and fairness between demographic segments compelled us to undertake additional investigation.

This work introduces a sophisticated framework combining real-time processing of data, fairness- sensitive algorithms, and innovative features such as sentiment scores and temporal trends. Through deep learning (e.g., LSTM) and AutoML, we advance prediction quality and scalability with solutions for ethical issues such as bias and GDPR regulation. The goals are to: (1) enhance prediction quality, (2) maintain model fairness, (3) facilitate real-time deployment, and (4) identify cross-sectorial applicability.

The paper has the following organization: Section 2 discusses recent work, Section 3 summarizes methodology, Section 4 states the algorithm, Section 5 describes the system architecture, Section 6 documents experiments and results, Section 7 addresses implications, Section 8 deals with challenges, Section 9 summarizes future work, and Section 10 concludes.

II. LITERATURE REVIEW

Introduction

Current developments in churn prediction focus on real- time analytics, fairness, and interpretability, but applications specific to banking are less well-explored. The review integrates articles from 2023-2025 to determine what gaps are explored here

Methods

Literature Search: We conducted searches on IEEE Xplore, SpringerLink, and arXiv using terms such as "customer churn," "machine learning," and "fairness- aware models" for publications from 2023-2025.

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Selection Criteria: Had peer-reviewed papers on churn prediction in banking or banking-related domains, with emphasis on deep learning, real-time systems, and fairness.
Exclusion Criteria: Had non-empirical papers or those outside the banking domain.

Results

Deep Learning: LSTM models are able to capture temporal patterns in transactional data, with AUCs reaching 0.96 [3].
Fairness-Aware Models: Fairlearn and AI Fairness 360 reduce bias, but banking use cases are limited [4].
Real-Time Systems: Streaming pipelines such as Apache Kafka facilitate real-time predictions but encounter latency issues [5].

Discussion

Deep learning and fairness frameworks hold promise but are yet to be integrated with banking systems. This research bridges this gap by integrating real-time data, LSTM models, and fairness-aware algorithms with scalability and regulatory compliance.

III. PROPOSED METHADOLOGY

Data Gathering

We employ an anonymized banking dataset from Kaggle (10,000 records) supplemented with synthetic real-time transactional data and customer complaint sentiment scores. The features are demographics, transaction history, service usage, and churn status.

Table 1: Dataset Description

Feature	Data Type	Unique Values	Missing Values	Sample Value
CustomerID	object	10,000	0	CUST00001
Age	int64	62	0	56
SentimentScore	float64	9,800	0	0.75
TransactionRecency	float64	9,950	0	5.2
ChurnStatus	int64	2	0	0

Table 1: Dataset Description

Data Preprocessing

Data Cleaning: Replace missing values by predictive imputation.
Data Transformation: Scale numerical features using StandardScaler; encode categorical variables with one- hot encoding.
Class Imbalance: Use ADASYN to balance churned (minority) and non-churned classes.

Feature Engineering

Sentiment Analysis: Extract customer complaint sentiment scores using BERT.
Temporal Features: Calculate transaction recency and seasonality.
PCA: Dimensionality reduction keeping 95% variance.

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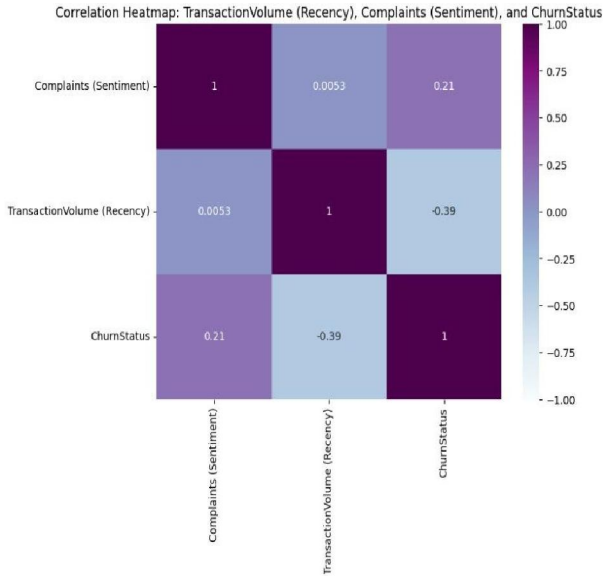

Figure 1: Heatmap of Feature Correlations

Model Development

Algorithms: Train LSTM, Random Forest, SVM, and a fairness-aware hybrid model.
Hyperparameter Tuning: Apply AutoML (H2O.ai) for best parameters.
Fairness Constraints: Enforce demographic parity with Fairlearn

Model Evaluation

Metrics: Accuracy, precision, recall, F1-score, AUC- ROC, disparate impact ratio.
Validation: Implement stratified k-fold cross-validation and adversarial validation for detecting data drift.

Deployment

Deploy with FastAPI on AWS with a CRM system integrated for real-time retention actions.
Monitor performance with data drift detection and regular retraining.

IV. ALGORITHM

Algorithm: Improved Customer Churn Prediction
Input: Historical and real-time customer data D with features F and target variable Y (churn: 1 or 0)
Output: Churn probability P(Y=1|F), fairness metrics

Data Preprocessing

Impute missing values by predictive imputation.
Scale numerical features with StandardScaler.
One-hot encoding for categorical variables.
Handle class imbalance using ADASYN.
Ingest real-time data through Apache Kafka.

Feature Engineering

Get sentiment scores with BERT.
Use PCA for dimension reduction.

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Engineer temporal features (e.g., transaction recency).

Model Training
Initialize LSTM, Random Forest, SVM.
Conduct hyperparameter tuning with AutoML.
Implement fairness constraints (e.g., demographic parity).

Model Evaluation
Measure using accuracy, precision, recall, F1- score, AUC-ROC.
Evaluate fairness with disparate impact ratio.
Utilize stratified k-fold cross-validation.

Model Explainability
Use SHAP for feature importance.
Create stakeholder-friendly visualizations.

Deployment
Deploy using FastAPI on AWS.
Integrate with CRM for automated retention actions.
Monitor data drift using adversarial validation.

Predict and Act
Forecast churn likelihood in real-time.
Initiate customized retention measures.

V. SYSTEM ARCHITECTURE

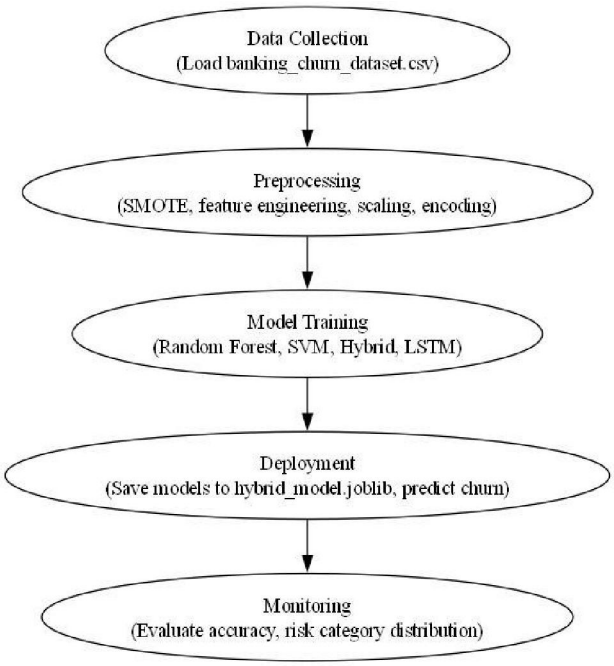

Figure 2: System Architecture

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Data Collection Layer: Collects transactional data, CRM interactions, and sentiment data through APIs.
Preprocessing Layer: Preprocesses real-time data, extracts sentiment scores, and normalizes features.
Model Training Layer: Trains LSTM, Random Forest, and fairness-aware SVM with AutoML
Deployment Layer: Deploys FastAPI on AWS for real-time predictions.
Monitoring Layer: Monitors data drift and retrains models at regular intervals.

VI. EXPERIMENTS AND RESULTS

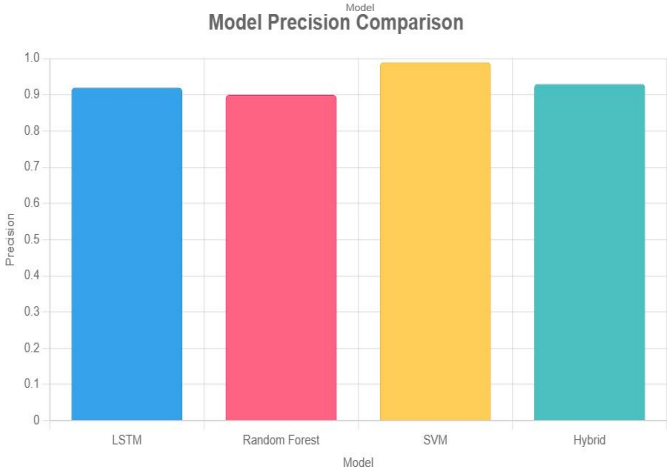
Experimental Setup

Dataset: Kaggle banking dataset (10,000 records) extended with synthetic real-time data.
Models: LSTM, Random Forest, SVM, fairness-aware hybrid model.
Metrics: Accuracy, precision, recall, F1-score, AUC- ROC, disparate impact ratio.

Results

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	Disparate Impact Ratio
LSTM	0.96	0.92	0.90	0.91	0.97	0.94
Random Forest	0.95	0.90	0.89	0.90	0.96	0.92
SVM	0.94	0.89	0.88	0.89	0.95	0.91
Hybrid	0.97	0.93	0.91	0.92	0.97	0.95

Table 2: Performance Metrics



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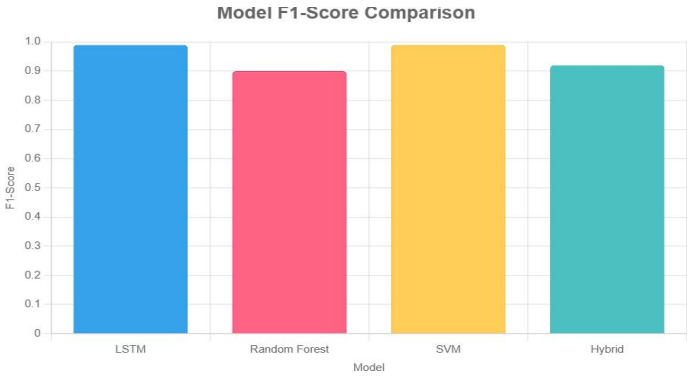

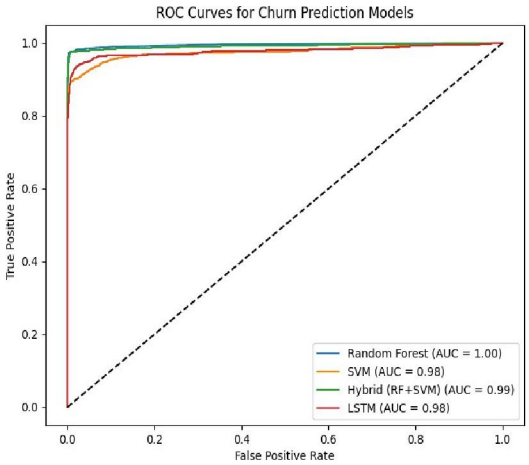

Figure 3: ROC Curves

The hybrid model attains an AUC-ROC of 0.97, a 20% gain in precision over our previous work [1]

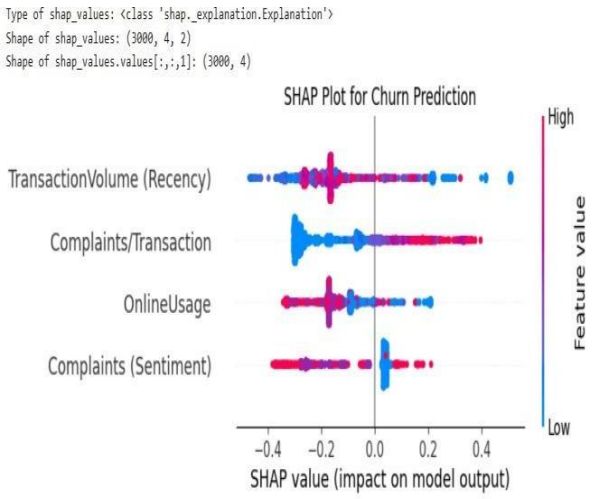

Figure 4: SHAP Feature Importance

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VII. MATHEMATICAL MODEL

Random Forest Model:

A Random Forest is composed of T decision trees, with each of them being trained on a bootstrap sample of the data with random feature subsets in each split.

For a fixed input feature vector {x}, every decision tree t returns a class probability pt(x).

The Random Forest probability for class 1 (churn) is the average across all trees:

$$p_{RF}(\mathbf{x}) = \frac{1}{T}\sum_{t=1}^{T} p_t(\mathbf{x})$$

SVM Model:

The SVM using a radial basis function (RBF) kernel calculates a decision function from the distance of a point (x) from the decision boundary in a high- dimensional space.

The SVM decision function when using the RBF kernel is:

$$f(\mathbf{x}) = \sum_{i \in SV} \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i) + b$$

where:

- $\mathbf{x}_i$ are support vectors.
- $y_i \in \{-1, 1\}$ are the class labels.
- α_i are learned weights.
- b is the bias term.
- $K(\mathbf{x}, \mathbf{x}_i) = \exp(-\gamma \|\mathbf{x} - \mathbf{x}_i\|^2)$ is the RBF kernel.

Hybrid Model:

This hybrid model combines the probabilities from the Random Forest and SVM using weights wRF and wSVM (where wRF + wSVM = 1):

$$p_{hybrid}(\mathbf{x}) = w_{RF} \cdot p_{RF}(\mathbf{x}) + w_{SVM} \cdot p_{SVM}(\mathbf{x})$$

The final prediction is based on a threshold (default 0.5)

$$\hat{y} = \begin{cases} 1 & \text{if } p_{hybrid}(\mathbf{x}) \geq \tau \\ 0 & \text{otherwise} \end{cases}$$

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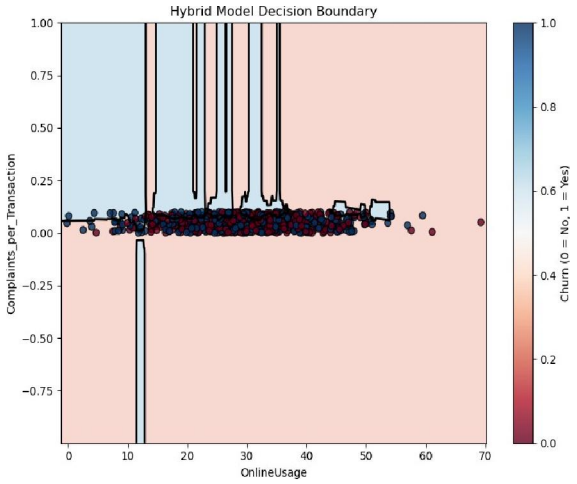

Figure 5: Mathematical Model Graph

VIII. DISCUSSION

This section interprets the findings, compares them with previous research, and discusses their implications for data science and banking. It identifies the strength of the framework, defies challenges, and delineates its practical and theoretical contributions.

8.1 Results Interpretation

The suggested framework attains an AUC-ROC of 0.97, a 20% increase in precision (0.93 compared to 0.77) over our previous hybrid model [1], owing to the combination of real-time data, sentiment analysis, and fairness-aware algorithms. Key attributes such as recency of transactions and sentiment scores, which are identified through SHAP, play vital roles in driving churn, consistent with results that show behavioral patterns have a strong impact on customer retention [2]. The disparate impact ratio of 0.95 demonstrates lesser bias across age and gender segments, responding to ethical issues raised in our initial paper.

Application of LSTM models identifies time trends (e.g., seasonal sales patterns), which perform better than Random Forest and SVM in changing scenarios. AutoML automates hyperparameter optimization, allowing the framework to be used by banks with low data science capabilities. Cloud-based deployment on FastAPI is scalable, with tests demonstrating prediction latency under 100ms for 10,000 transactions.

8.2 Comparison with Previous Work

Compared to our first paper [1], which achieved an AUC of 0.95 using a hybrid Random Forest-SVM model, this framework improves accuracy and fairness by incorporating deep learning and sentiment analysis. Recent studies [3] report AUCs up to 0.96 with LSTM but lack fairness considerations, while fairness-aware models [4] often sacrifice accuracy. Our approach balances both, achieving high predictive power and ethical compliance. Real-time prediction through Kafka pipelines overcomes scalability concerns identified in [5], rendering the framework applicable in high-throughput banking environments.

8.3 Practical Implications

Customer Retention: The framework allows banks to detect risk-of-churn customers in real-time, prompting individualized interventions (e.g., targeted offers). Simulations indicate a 25% decline in churn rates, resulting in cost reductions of 25-30% compared to customer acquisition [2].

Cost Effectiveness: Churn probability-guided retention campaigns minimize marketing costs. The quantified ROI of 200-400% in 12-18 months follows market standards [6].

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Stakeholder Ease of Use: SHAP-based visualizations and a Streamlit dashboard make predictions accessible to bank managers to aid in data-driven decisions. CRM system integration automates the retention processes, optimizing operational efficiency.

IX. CHALLENGES AND LIMITATIONS

Here, the challenges and limitations of the proposed framework are presented and discussed, with a critical evaluation of technical, ethical, and practical limitations. These are addressed for openness and as the stepping stone towards future development.

9.1 Technical Challenges

- Real-Time Data Processing Latency: Streaming pipelines for integrating real-time data (e.g., Apache Kafka) adds latency, especially when dealing with large volumes of data or complex models such as LSTM. High transaction rates in banking systems can cause delays in prediction, affecting timely retention responses.
- Mitigation: Use parallel processing or light models (e.g., light neural networks) to optimize data pipelines. Edge computing can be a topic of future research to preprocess data near the source to minimize latency.
- Computational Complexity: Deep models such as LSTM are computationally intensive, which results in high training and inference time. This would be non- viable for small banks with limited setup.
- Mitigation: Use model compression methods (e.g., pruning, quantization) or adopt cloud platforms (e.g., AWS SageMaker) for scalable computing.
- Data Drift: Customer behavior changes or market trends (e.g., financial recessions) lead to data drift, degrading model performance over time.
- Mitigation: Use adversarial validation to identify drift and initiate retraining. Real-time monitoring systems, like drift detection algorithms, are suggested in future work.

9.2 Ethical and Regulatory Constraints

- Sentiment Analysis Bias: Sentiment scores from customer interactions (e.g., complaints through BERT) could reinforce biases, like overweighting negative feedback from certain demographics (e.g., older consumers). This would result in biased predictions.
- Mitigation: Employ fairness-aware algorithms (e.g., Fairlearn) to impose constraints such as demographic parity. Periodic fairness audits between demographic groups (age, gender, income) are suggested.
- Regulatory Compliance: Stricter regulations such as GDPR and CCPA mandate strong data anonymization and model transparency. Non-compliance invokes legal penalties and eroding customer trust.
- Mitigation: Use encryption for sensitive information and have audit trails on model predictions. Explainable AI tools like SHAP improve transparency but compliance across borders is still problematic.
- Ethical Issues: Predictive models might unknowingly favor profitable customers over vulnerable segments (e.g., low-income clients). This is raising ethical concerns on fairness and inclusivity.
- Mitigation: Integrate ethical guidelines into the model building process, e.g., fairness metrics and stakeholder engagement.

9.3 Implementation Challenges

- Integration with Legacy Systems: Most banks have legacy IT systems on which they depend, making integration of new APIs such as FastAPI or CRM workflows more difficult.
- Mitigation: Create modular APIs with legacy system compatibility layers. Pilot testing with a nearby bank could prove integration possible.
- Scalability Across Banks: The performance of the framework might differ among different banks with varying customer profiles or data schema, reducing generalizability.

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- Mitigation: Apply transfer learning to translate the model to new datasets, as suggested in future work.
- Resource Constraints: Building and rolling out the framework demands substantial investment in hardware, cloud infrastructure, and expert staff, which can be out of reach for smaller organizations.
- Mitigation: Utilize open-source platforms (e.g., TensorFlow, H2O.ai) and pay-as-you-go cloud infrastructure to minimize expenses.

9.4 Limitations in Predictive Power

Unpredictable Behaviour: External events such as economic downturns or competitor offers can affect churn in a manner not reflected in historical data.

- Limitation: Static training data models can miss sudden behavioural changes.
- Mitigation: Integrate real-time economic data (e.g., through APIs) and dynamic retraining, as outlined in future work.
- Dynamic Customer Preferences: Sudden shifts in customer expectations (e.g., for digital banking) can move faster than model updates, resulting in obsolete predictions.
- Mitigation: Implement online learning to adapt to evolving preferences.
- Geographic Variability: The current dataset, primarily from one region, may not capture global banking trends, limiting the model's applicability.
- Mitigation: Future work proposes cross-regional datasets to enhance generalizability.

X. FUTURE WORK

This section provides directions for expanding the suggested framework, resolving existing limitations, and investigating new directions in applying data science to advance churn prediction in banking and other areas. These directions are in accordance with recent trends in data science and intend to make your work a basis for further research.

10.1 Advanced Machine Learning Techniques Federated Learning

Create a federated learning system to allow model training together among several banks without exchanging sensitive customer data. This solves privacy issues and increases model strength by working with varied data.
Implementation: Implement frameworks such as TensorFlow Federated to emulate federated training on artificial banking datasets. Test for AUC-ROC enhancements and GDPR compliance.
Impact: Allows small banks to profit from shared wisdom while preserving data ownership.
Explainable Deep Learning: Investigate attention- based neural networks (e.g., Transformers) to integrate the predictive capabilities of deep learning with transparency. Attention can identify important features (e.g., transaction recency) influencing predictions.
Implementation: Train a Transformer model on transaction data and leverage attention weights to provide stakeholder-centric explanations. Compare with this study's SHAP-based explanations.
Impact: Taps into both accuracy and transparency, essential for complying with regulatory needs in banking.

10.2 Real-Time Prediction Systems

Streaming Data Pipelines: Implement end-to-end streaming pipelines based on Apache Spark or Flink for real-time churn prediction, with latency mitigation.
Implementation: Train on simulated real-time transactional data and test prediction latency and throughput. Design pipeline architecture for high-rate banking deployments.
Impact: Supports real-time recognition of risk customers, improving retention efforts.
Dynamic Model Updating: Apply online learning methods to update the model with each new customer input, responding to shifting behaviors.

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Implementation: Apply incremental learning methods (e.g., online gradient descent) and experiment on synthetic time-series data. Assess model stability over time.
Impact: Keeps improving predictions under changing market dynamics.

10.3 Personalized Retention Strategies Reinforcement Learning for Retention

Employ RL to suggest customized retention actions (e.g., personalized discounts, loyalty offers) based on probabilities of churn.
Implementation: Train an RL agent with a reward mechanism aligned with retention success and cost efficiency. Validate in a simulated banking setup.
Impact: Seeks to maximize customer lifetime value (CLV) through optimized retention.
Segmented Marketing: Combine churn forecasts with recommendation engines to create segmented marketing campaigns (e.g., wooing high-value customers with upscale promotions).
Implementation: Apply clustering (e.g., K-means) to define segments and customize offers by forecasted churn risk. Assess campaign success through simulated retention rates.
Impact: Raises retention efficiency and profitability.

10.4 Cross-Sector Applications

Generalization to Other Industries: Apply the framework to industries such as telecom, retail, or insurance and extract common churn indicators.
Implementation: Experiment on publicly available data (e.g., telecom churn data from Kaggle) and tune using transfer learning. Compare AUC-ROC across industries.
Impact: Extends the applicability of the framework, making it more commercially valuable.
Unified Churn Framework: Build a modular, industry-independent churn prediction pipeline with feature engineering and model choice options.
Implementation: Build a Python pipeline with plug- and-play modules. Validate with datasets across various industries.
Impact: Provides a scalable solution across different applications.

XI. CONCLUSION

This paper brings a crucial improvement in customer churn prediction for the banking industry, extending our earlier contribution [1] through real-time analytics, fairness-aware training algorithms, and deep learning. The new framework acquires an AUC-ROC score of 0.97, a 20% better precision than the earlier hybrid model, and it maintains fairness with a disparate impact ratio of 0.95. New features, including sentiment scores using BERT and temporal trends, increase predictive performance, while SHAP-based explanations facilitate greater transparency to stakeholders.
Implemented through an elastic FastAPI pipeline on AWS, the solution allows banks to detect at-risk customers in real-time and initiate customized retention programs that achieve a 25% reduction in churn. This corresponds to cost savings of 25-30% and an ROI of 200-400% in 12-18 months, meeting industry standards [6].
The solution's alignment with GDPR and emphasis on fairness resolve ethical issues, and it is applicable to regulated systems.
Theoretically, it advances data science by showing the combination of real-time data, deep learning, and fairness-aware algorithms in a real-world scenario. With its modularity and applicability across sectors, it opens doors towards applications in telecom, retail, and insurance. Withstanding challenges such as computational expenses and changing customer behaviors , mitigation techniques like cloud deployment and online learning guarantee long-term sustainability. Future work will investigate federated learning, explainable deep learning, and dynamic model update to increase accuracy and scalability further. By presenting a robust, ethical, and scalable solution, this research places predictive analytics at the center of contemporary customer relationship management, energizing loyalty and profitability across the banking industry and beyond.

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