# Multi-Domain Customer Churn Prediction using Transfer Learning

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## ABSTRACT

Customer Churn Prediction is a task that analyses or identifies the customers who are likely to stop using the product,service,or subscription in the near future using data analytics and machine learning techniques. By analyzing customer behavior, transaction history, and engagement metrics, businesses can proactively intervene to retain at-risk customers, thereby reducing revenue loss and improving customer lifetime value. This project focuses on multi-domain churn prediction using transfer learning, which enables knowledge transfer from data-rich domains to data-scarce domains to improve the prediction accuracy. This study aims to improve churn prediction accuracy across multiple domains using transfer learning. For example, telecom dataset(data-rich) and data-scarce domains may be like new streaming services or new bank services. In this approach, the model is pre- trained on a known large labeled source dataset to learn customer behavior patterns. This model then fine-tuned on a smaller target domain dataset, optimizing for specific churn indicators in the new domain. The results demonstrate that the it shows better prediction accuracy and generalization compared to the models trained on the target dataset, the transfer learning improves churn prediction performance in data-scarce by learning the knowledge from the data-rich domains. By enabling accurate churn prediction across different industries and also assisting businesses in reducing customer churn and improving long-term customer retention.

**Keywords:** Customer-Churn prediction, Transfer learning, cross-domain learning, neural networks, Explainable AI,Banking Analytics, Telecom Analytics

## INTRODUCTION

Customer retention is an important issue for companies. It usually costs more money for companies to attract new customers than to keep their existing customers. Because of this, customer churn prediction has become very important. Customer churn usually happens when a customer avoids using a company's service or ends their relationship with the company. If companies can identify customers who are likely to leave, they can take steps to keep them and reduce loss of customers.

In recent years, machine learning methods are used to study customer behavior and predict their churn rate. These methods use past customer data to detect patterns that show whether a customer might stop using a service. Different algorithms such as logistic regression, decision trees, random forests, and neural networks are commonly used for this purpose. These models help companies to understand customer behavior better .

Even though there are many machine learning models that are successful in churn prediction, some challenges still exist. One such challenge is the limited amount of labeled data available in some industries. When there is not enough data, it becomes very difficult to train accurate prediction models. Another challenge is that many models are trained using only one dataset or one domain. Because customer behavior can be different across industries, a model that works well in one domain may not perform well in another.

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Another limitation in many existing studies is that models are usually built from scratch for each dataset. This means that useful knowledge learned from similar datasets is not used. As a result, it is an opportunity to improve churn prediction by using information from related domains. This idea is known as cross-domain learning.

To address these challenges, this study proposes a churn prediction approach based on transfer learning. In this technique, a neural network model is trained on a telecom dataset of their customers so that it can identify general patterns of customer behavior. Then, the knowledge is transferred to a banking dataset, the model is further trained to predict churn rate in the banking sector. This approach helps improve prediction performance, especially when the target dataset is small.

The main goals of this research are as follows. First, a transfer learning framework is proposed to improve churn prediction using knowledge from multiple domain datasets. Second, the approach includes data preprocessing, feature alignment, and deep learning techniques to make telecom and banking datasets compatible.

The rest of the paper is organized as follows. Section 2 is about the work on customer churn prediction. Section 3 is about explaining the proposed methodology and model design. Section 4 is about the datasets and preprocessing methods. Section 5 is about the experimental setup and details of implementation. Section 6 is about the results and performance evaluation. Finally, Section 7 provides the conclusion and possible future research directions.

## METHODOLOGY

This section describes the research methodology used to develop a multi-domain customer churn prediction model using transfer learning. The approach involves dataset preparation, data preprocessing, feature alignment, knowledge transfer and adaptation, validation and output. Each stage is designed to ensure consistent experimental conditions and reliable evaluation. The goal is to determine whether behavioral knowledge learned from telecom customer data can support churn prediction in the banking domain. The methodology also considers dataset imbalance, standardized preprocessing, and consistent evaluation using classification metrics.

### Dataset Preparation

In this study, two publicly available customer churn datasets were considered for cross-domain churn prediction. The IBM Telco Customer Churn dataset was used as the source domain, containing 7,043 customer records and 21 columns, with an approximate churn rate of 26.5%. The Bank Customer Churn Prediction dataset was used as the target domain, containing 10,000 customer records and 14 columns, with an approximate churn rate of 20.4%. The telecom dataset contains service and account attributes, while the banking dataset contains demographic, account, product, and activity attributes. Using datasets from different industries provides a basis for evaluating whether behavioral representations can be adapted across related churn prediction tasks.

### Dataset Pre- processing

Before model training, preprocessing was performed to improve data quality and consistency. Irrelevant identifier attributes were removed, while categorical variables were converted into numerical representations using encoding techniques. For the banking dataset, Geography and Gender were one-hot encoded, producing 11 input features after removing the Exited target variable. Numerical features were standardized using StandardScaler, with the scaler fitted only on the training data and subsequently applied to the test data. The banking experiment used an 80:20 train-test partition, producing 8,000 training records and 2,000 test records. These procedures provide consistent feature representations while reducing the possibility of information leakage during evaluation.

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**Knowledge transfer and Adaptation**

**Feature Alignment**

Feature alignment was necessary because the telecom and banking datasets contain different feature names, scales, and domain-specific meanings. Therefore, the variables were not treated as literal equivalents; instead, related customer-behavior concepts were identified using semantic and domain knowledge. The alignment focuses on shared behavioral constructs such as tenure, engagement, complaints, financial exposure, and activity. This representation provides a common feature space for transfer while acknowledging the differences between the two industries [6][9].

Techniques used for feature alignment:

**Semantic Feature Mapping:**

➢identified behaviorally related features between telecom and banking datasets based on their role in customer engagement and churn.

➢For example:

– Account length : Tenure (customer relationship duration)

-- Customer Service Calls : Complain (service dissatisfaction indicator)

**Domain Knowledge-Based Mapping:**

● Domain knowledge was used to compare the behavioral role of customer attributes across industries rather than assuming direct variable equivalence.

● Engagement, complaints, financial exposure, and activity indicators were compared between domains to identify related behavioral representations for prediction.

**Feature Selection:**

Behaviorally relevant features associated with customer retention were selected to construct a more consistent representation and support cross-domain transferability.

**Feature Renaming for Structural Consistency**

To provide a consistent input structure for transfer learning, aligned banking variables were represented using the corresponding behavioral feature definitions rather than treating the original domain-specific names as identical.

**Data Preprocessing and Scaling**

The feature distributions were comparable and evaluations are also seen, by applying StandardScaler normalization to both datasets.

TABLE I Example Feature Alignment Table

| **Telecom Feature** | **Banking Feature** | **Behavioral Interpretation** |
|---|---|---|
| Account length | Tenure | Customer relationship duration |
| Total day charge | Balance | Financial exposure indicator |
| Service Calls | Complaints | Service dissatisfaction indicator |

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| | | |
|---|---|---|
| Plan | HasCrCard | Product/service engagement |
| Voice Mail plan | IsActiveMember | Customer activity indicator |

**Baseline Model Development**

The baseline churn prediction model was developed using an Artificial Neural Network (ANN) trained exclusively on the banking dataset. The validated banking implementation used 11 preprocessed input features followed by dense layers with ReLU activation and dropout regularization, with a sigmoid output layer for binary classification. The model was trained using the banking training partition without transferring weights from the telecom domain, providing a single-domain benchmark for comparison. This baseline establishes the performance of learning directly from the target-domain data before considering cross-domain adaptation.

**Transfer Learning Implementation**

The primary contribution of this research lies in the application of transfer learning for cross-domain churn prediction. The proposed framework first trains a neural network on the telecom source domain to learn general customer-behavior representations associated with churn. The learned representations are then used to initialize the corresponding banking model before target-domain adaptation. Rather than treating the telecom and banking variables as identical, the transfer process operates on the aligned behavioral representation. Selected learned layers are retained while target-domain parameters are adapted through fine-tuning. This strategy provides a structured mechanism for reusing behavioral knowledge across related churn prediction tasks.

**Model Fine Tuning**

After transferring the learned representations, the model was fine-tuned using the banking training data. A reduced learning rate was used during adaptation so that the transferred parameters could be adjusted gradually to target-domain characteristics. The transfer configuration described in the framework uses selective layer freezing, retaining lower-level behavioral representations while allowing later representations to adapt to banking-specific patterns. Class imbalance was also considered during model training so that minority churn cases were not ignored during optimization.

For the banking evaluation, the dataset contained 10,000 records, of which 8,000 were used for training and 2,000 for testing. Categorical variables were encoded before numerical standardization, and the scaler was fitted using the training partition only. The validated banking ANN used the Adam optimizer with binary cross-entropy loss, a batch size of 32, and a maximum of 150 training epochs with 20% of the training partition used for validation. The final model was evaluated once on the held-out 2,000-record test set.

**Validation and Output**

**Performance Evaluation**

Finally, model performance was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. These measures provide complementary information about overall correctness, minority-class detection, classification balance, and ranking performance. The baseline and transfer-learning results were evaluated on the banking test partition so that both approaches could be assessed using the same target-domain evaluation set. The reported classification results therefore focus on the held-out banking data rather than training performance.

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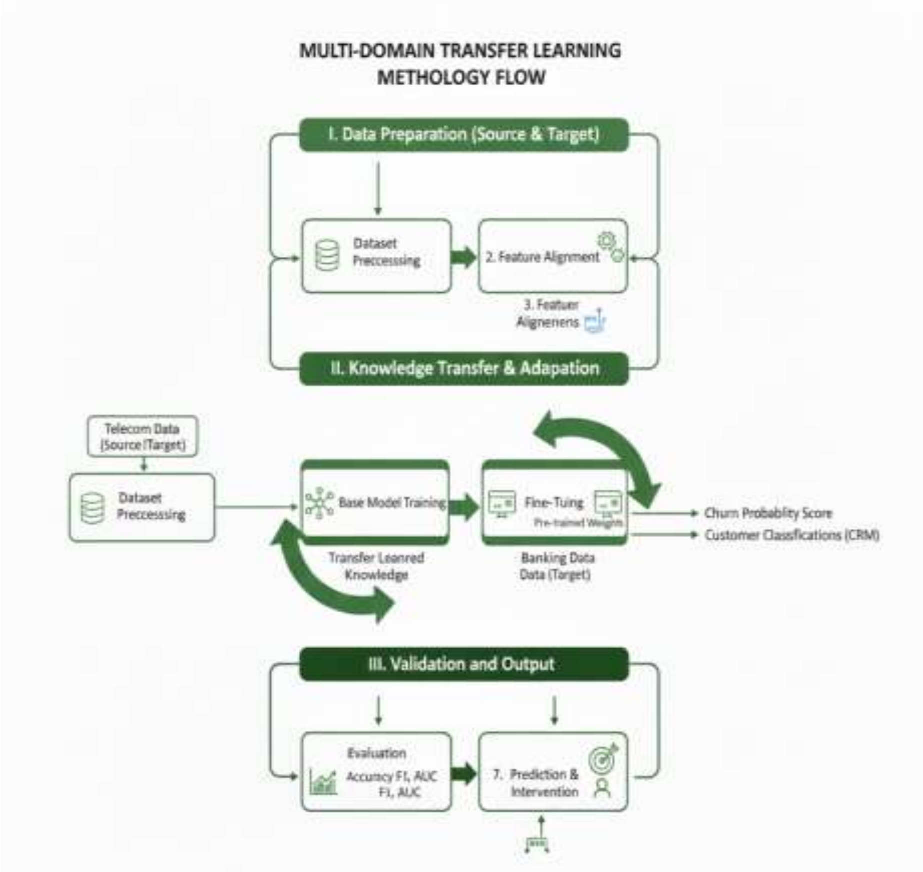


## LITERATURE SURVEY

Customer churn prediction is widely used because it's important for managing customer relationships. Previous models use statistical and machine learning methods to analyze customer behavior and to predict churn probability.Although these models were easy to understand, they often had trouble capturing complex relationships between different customer features.

Afterwards studies introduced ensemble learning methods such as Random Forest and Gradient Boosting, which improved prediction by combining multiple classifiers. These approaches demonstrated better performance in identifying churn patterns related to customer tenure, billing information, and service usage behavior.

With development in artificial intelligence, researchers began adopting Artificial Neural Networks(ANNs) for churn prediction tasks. Neural network- based models proved effective in capturing nonlinear dependencies among multiple features and achieved improved classification accuracy compared to traditional models. Although these advantages, deep learning approaches mostly demand high computational resources and important volumes of labelled data, which may not always be available in real-world business environments. [4][5]

Domain-specific churn prediction studies in industries such as telecommunications and banking have also highlighted important behavioural signs influencing customer maintenance. Telecom-focused research emphasized service usage patterns, complaint frequency, and subscription plans, while banking studies focused on financial engagement indicators such as account balance, transaction activity, and product utilization. Although these domain-dependent models achieved promising results, they often lacked the ability to generalize across different industries, limiting their practical applicability. [6][7]

In recent times,researchers have examined transfer learning techniques to improve predictive performance by utilizing knowledge learned from related datasets. Transfer learning has shown potential in improving model generalization and decreases the dependency on large target-domain datasets. However, its application in

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customer churn prediction remains relatively under-examined compared to other fields such as computer vision and natural language processing. [8][9]

Therefore, a major research gap is present in developing multi-domain churn prediction frameworks that effectively involves behavioural knowledge across industries. To address this limitation, the present study provides a transfer learning-based neural network model that uses telecom(source-dataset) customer behaviour knowledge to enhance churn prediction accuracy in the banking(target-dataset) domain. By giving access to cross-domain knowledge reuse, the proposed approach targets to achieve better classification balance and improved predictive reliability.[1][4][10]

## RESULTS

This section presents the results obtained from the proposed churn prediction framework. The performance of the transfer-learning model was evaluated against a baseline neural network trained only on the banking dataset. Both approaches were assessed on the same held-out banking test set using standard classification measures, including accuracy, precision, recall, F1-score, and ROC-AUC. The detailed classification reports are used as the final reported results to provide a consistent basis for comparison between the baseline and transfer-learning approaches.

The baseline neural network model focuses only on the banking dataset without using transfer learning. In contrast, the proposed model follows a transfer-learning approach in which behavioral representations learned from the telecom source domain are adapted to the banking target domain. Both approaches are evaluated on the same held-out banking test set. The final classification report shows that the baseline model achieved 49% accuracy, while the transfer-learning model achieved 86% accuracy. The corresponding ROC-AUC values were 0.770 and 0.869, respectively, indicating improved discrimination in the reported transfer-learning evaluation.

**Evaluation Metrics**

While building an ML model it is important to understand how well they perform. So evaluation matrix is used to quantify model performance, enabling comparison and validation against specific goals.

For the classification matrix, the problems aim to predict discrete categories. To evaluate the performance of classification models, we use Accuracy, Precision, Recall, F1-score, Logarithm loss.

- Accuracy = Number of correct predictions/ Total number of Predictions
- Precision = TP/TP+FP
- Recall = TP/TP+FN
- F1-score=2*(Precision*Recall)/(Precision*Recall)

TP-TruePositive,FP-False Positive,FN-False Negative

TABLE II

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Logistic Regression | 82% | 0.79 | 0.74 | 0.76 |
| Random Forest | 89% | 0.86 | 0.82 | 0.84 |
| Baseline Neural Network | 49% | 0.26 | 0.78 | 0.39 |
| Proposed Transfer Learning Model | 86% | 0.85 | 0.39 | 0.54 |

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The transfer-learning model improves substantially over the banking neural-network baseline in overall accuracy and precision, while the F1-score also increases from 0.39 to 0.54 for the churn class. However, the Random Forest model achieves higher overall accuracy, indicating that transfer learning should be viewed as a complementary approach rather than a universally superior classifier.

**Confusion Matrix Analysis**

A confusion matrix is a table used to evaluate the performance of a classification model by comparing actual target values made by the model with predicted values and showing where the model was right or wrong. This helps us to understand where the model is making mistakes so you can improve it . The confusion matrix provides a detailed breakdown of predicted and actual churn classes and the predictions are classified into 4 categories: true positive(TP), true negative(TN), false positive(FP), false negative(FN).

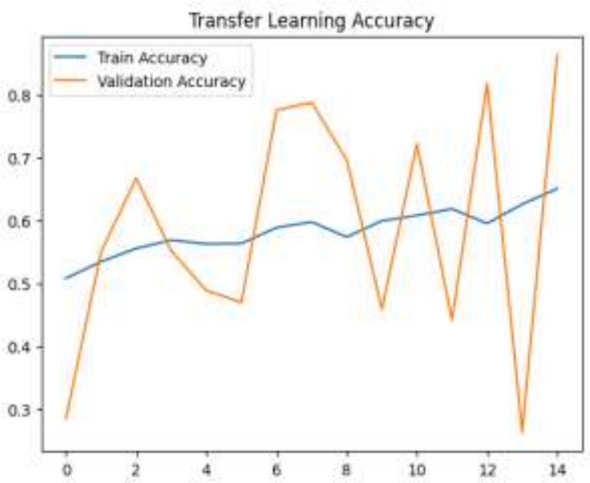
TABLE III

| | **Predictive Positive** | **Predictive Negative** |
|---|---|---|
| Actual Positive | True Positive(TP) | False Negative(FN) |
| Actual Negative | False Positive(FP) | True Negative(TN) |

The classification results indicate that the transfer-learning model produces a substantially different error profile from the baseline. The baseline achieves high recall for the churn class but has low precision, resulting in many false-positive churn predictions. The transfer-learning model improves precision considerably while retaining measurable churn detection capability. Therefore, the model provides a more selective classification pattern, although the lower churn-class recall indicates that further threshold tuning may be required for retention-focused applications.

**Performance Graph Analysis**

The performance graph analysis in machine learning is highlighting the model's behaviour by visual tools like ROC curves for classifying and learning curves for identifying over-fitting or under-fitting. It will also help the model to detect issues related to model optimization. Key graphs include the learning curves showing training and validation error epochs, ROC curves that are used in representing sensitivity versus specificity, and confusion matrices evaluating the accuracy for ensuring that the models generalize effectively to new data.




The training and validation curves provide a visual indication of the model's learning behavior across epochs. The curves can be used to examine changes in training and validation loss and accuracy and to identify possible divergence between training and validation performance. Such divergence would indicate potential

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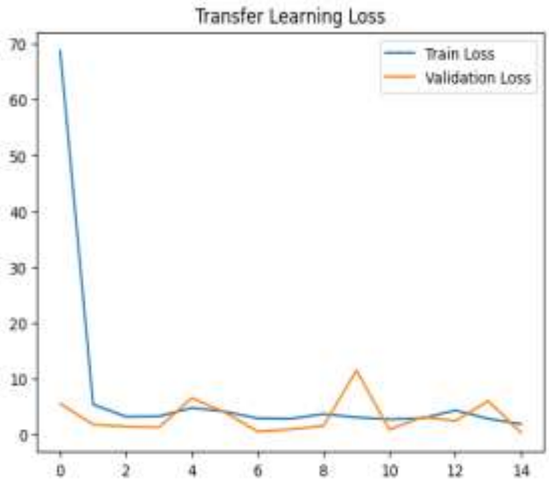
overfitting, while similar trends would suggest more stable generalization. The final evaluation, however, is based on the held-out test set rather than the training curves alone.




Furthermore, ROC curves were used in evaluating the model's effectiveness in distinguishing between churn and non-churn classes.The area under the ROC curve(AUC) stayed high, denoting strong classification performance.

## RESULTS DISCUSSION

The reported results show that the transfer-learning strategy improves the banking neural-network baseline in overall accuracy and precision. By adapting behavioral representations from the telecom source domain to the banking target domain, the proposed approach provides evidence that related customer-behavior information can support cross-domain churn prediction. The improvement should be interpreted specifically relative to the banking ANN baseline rather than as superiority over every conventional machine-learning classifier.

=== Baseline Report ===

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.88 | 0.42 | 0.57 | 1592 |
| 1 | 0.26 | 0.78 | 0.39 | 408 |
| accuracy | | | 0.49 | 2000 |
| macro avg | 0.57 | 0.60 | 0.48 | 2000 |
| weighted avg | 0.75 | 0.49 | 0.53 | 2000 |

Baseline AUC: 0.7704576805596611

=== Transfer Learning Report ===

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.86 | 0.98 | 0.92 | 1592 |
| 1 | 0.85 | 0.39 | 0.54 | 408 |
| accuracy | | | 0.86 | 2000 |
| macro avg | 0.86 | 0.69 | 0.73 | 2000 |

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weighted avg 0.86 0.86 0.84 2000

Transfer Learning AUC : 0.8688763979209775

TABLE V

| | Actual | Predicted_ Probability | Predicted_ Class |
|---|---|---|---|
| 0 | 0 | 0.014589 | 0 |
| 1 | 0 | 0.060003 | 0 |
| 2 | 0 | 0.054546 | 0 |
| 3 | 1 | 0.579358 | 1 |
| 4 | 0 | 0.091256 | 0 |
| 5 | 1 | 0.171543 | 0 |
| 6 | 1 | 0.345155 | 0 |
| 7 | 0 | 0.041666 | 0 |
| 8 | 0 | 0.017923 | 0 |

The baseline neural network model showed high recall but low precision for the churn class, indicating that many customers were classified as potential churners even when they belonged to the non-churn class. In contrast, the proposed transfer-learning model substantially improved churn-class precision from 0.26 to 0.85, while its recall decreased from 0.78 to 0.39. Consequently, the transfer-learning model achieved a higher churn-class F1-score of 0.54 compared with 0.39 for the baseline, reflecting a more selective rather than uniformly stronger classification behavior.

TABLE IV

| | Actual | Churn_ Probability | Risk_ Level |
|---|---|---|---|
| 0 | 0 | 0.014589 | Low Risk |
| 1 | 0 | 0.060003 | Low Risk |
| 2 | 0 | 0.054546 | Low Risk |
| 3 | 1 | 0.579358 | Medium Risk |
| 4 | 0 | 0.091256 | Low Risk |

By utilizing behavioral representations from a related industry, the reported results indicate that multi-domain transfer learning can improve the banking neural-network baseline. The approach increases overall accuracy and precision in the reported evaluation, while the ROC-AUC also improves from 0.770 for the baseline to 0.869 for the transfer model. These findings support further investigation of cross-domain learning for customer retention applications.

## DISCUSSION

The results from this study indicate that the proposed transfer-learning-based churn prediction model performs better than the banking neural-network baseline in overall accuracy, precision, and ROC-AUC. The improvement is consistent with the proposed idea of reusing behavioral representations learned from a related source domain. However, the results do not establish superiority over every conventional classifier, since the Random Forest baseline reports higher overall accuracy. Therefore, the contribution of the proposed approach is better characterized as cross-domain knowledge reuse rather than universal classifier superiority.[3][5][8]

A pattern observed during experimentation is that the baseline model showed high recall but low precision for the churn class, indicating that it classified many customers as potential churners. Although this behavior helps detect a larger proportion of actual churn cases, it also increases false-positive predictions and may affect

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retention decisions. In contrast, the proposed transfer-learning model considerably improved precision, although its churn-class recall was lower than the baseline. The resulting increase in churn-class F1-score from 0.39 to 0.54 indicates improved precision-recall balance under the reported evaluation setting.[3][8][12]

Another observation is that cross-domain representations may provide useful information for the target banking task. Customer behavioral patterns can share broad characteristics across industries, including relationship duration, engagement, activity, and dissatisfaction. The reported improvement in ROC-AUC suggests that the transferred representation can help distinguish churn outcomes in the target domain. Nevertheless, additional repeated experiments and validation across datasets are required before making a broader claim about generalization across industries.

The findings of this study are consistent with prior research highlighting the effectiveness of machine learning techniques for churn prediction. Earlier work has shown that neural network–based models are well suited for capturing complex, nonlinear relationships among customer attributes. The reported results support these observations and indicate that multi-domain knowledge transfer can provide an additional modeling strategy when the target domain has limited or differently structured behavioral information. [7][11]

This model introduces a more practical and user-oriented perspective to technological applications, improving the way everyday challenges are addressed. Organizations can leverage transfer learning techniques to enhance churn prediction accuracy, even in situations where domain-specific data is limited. This supports the development of stronger customer relationships, more effective retention strategies, optimized marketing efforts, and efficient resource utilization. By accurately identifying customers at risk of churn, businesses can implement targeted retention measures to improve customer satisfaction and minimize revenue loss.

In summary, the discussion highlights that transfer learning offers a promising approach for developing cross-domain churn prediction systems. Reusing representations from a related source domain can provide an alternative to training the target model entirely from scratch, while the reported evaluation shows improvement over the banking neural-network baseline. Future improvements include repeated validation, larger multi-domain datasets, stronger feature-alignment studies, advanced deep learning techniques, and real-time prediction systems.

## CONCLUSION

This paper presents a multi-domain customer churn prediction framework based on transfer learning across telecommunications and banking domains. Conventional churn models are generally trained independently for each dataset, which limits direct reuse of learned behavioral representations when moving to another industry. To address this limitation, the proposed framework investigates the use of behavioral knowledge learned from a telecom churn dataset and its adaptation to a banking churn prediction task.

The reported experimental results show that the transfer-learning model improves overall accuracy, precision, and ROC-AUC compared with the banking neural-network baseline. The transfer model achieved 86% accuracy and an ROC-AUC of approximately 0.869, compared with 49% accuracy and an ROC-AUC of approximately 0.770 for the baseline. However, the Random Forest comparison indicates that transfer learning is not universally superior to conventional classifiers. These findings suggest that behavioral knowledge from related domains can provide useful additional information for churn prediction.

This study indicates that transfer learning has potential for customer retention applications by enabling behavioral representations from one industry to be adapted to another. The proposed framework can support proactive decision-making and targeted retention strategies when domain-specific data or modeling resources are limited. However, practical deployment should be preceded by validation on larger and independently collected datasets to confirm the stability and transferability of the reported results.

Future research can extend the framework using larger multi-industry datasets, repeated experiments, cross-validation, confidence intervals, and more rigorous empirical studies of feature alignment. Advanced deep learning architectures and real-time churn prediction systems can also be investigated. Moreover, cloud-based

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deployment and explainable AI techniques may further improve the applicability, transparency, and scalability of the proposed framework.

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