CUSTOMER CHURN PREDICTION BY USING DEEP LEARNING

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ABSTRACT: Customer churn is a significant business challenge in the telecommunication industry, where losing existing customers directly reduces revenue and increases acquisition costs. Retaining customers is far more cost-effective than acquiring new ones, making early and accurate churn prediction a strategic priority. Traditional machine learning models such as Logistic Regression, SVM, and Random Forest fail to capture complex non-linear patterns in high-dimensional telecom datasets and require extensive manual feature engineering. While deep learning models overcome these accuracy limitations through automatic feature extraction, they suffer from a critical interpretability gap — predictions cannot be explained to business stakeholders. This project proposes ChurnNet-XAI, a hybrid deep learning architecture that integrates 1D Convolutional Neural Networks (CNNs) for sequential feature extraction, Residual Blocks for stable gradient learning, Squeeze-and-Excitation (SE) modules for channel-wise attention, and Spatial Attention mechanisms for position-wise feature emphasis. The model is evaluated on three benchmark telecom datasets — IBM Telco, Churn-in-Telecom, and UCI Churn — achieving accuracy of 95.59%, 96.94%, and 97.52% respectively. Class imbalance is handled using SMOTE, SMOTEEN, and SMOTETomek, with SMOTEEN consistently outperforming other techniques. Critically, Explainable AI (XAI) tools including SHAP, LIME, and Integrated Gradients are incorporated to transform opaque predictions into actionable business intelligence. The system enables telecom operators to understand not only who will churn, but why — supporting targeted, evidence-based customer retention strategies.

Keywords: Customer Churn Prediction, Deep Learning, 1D CNN, Residual Block, Squeeze-and-Excitation, Spatial Attention, Explainable AI, SHAP, LIME, SMOTE, Telecommunication Industry.

1. INTRODUCTION

The telecommunication industry operates in one of the most competitive and rapidly evolving markets in the world. Customers today can switch service providers with minimal effort — a few taps on a smartphone are all it takes. When they leave, the financial consequences are immediate and significant. Industry research consistently shows that acquiring a new customer costs anywhere from five to ten times more than retaining an existing one. This asymmetry makes customer churn prediction not just a technical problem, but a strategic imperative for every telecom operator.

Customer churn refers to the phenomenon where a customer discontinues their service subscription and migrates to a competing provider. Unlike a sudden event, churn is a gradual process that builds through accumulated dissatisfaction — unresolved service complaints, billing surprises, or simply an attractive offer from a competitor. By the time a customer has churned, the opportunity to intervene has already passed. The goal of a churn prediction system is therefore to identify at-risk customers before they leave, providing the telecom operator with a window to act.

Traditional machine learning models such as Logistic Regression, Support Vector Machines (SVM), and Random Forests have been widely applied to churn prediction. While these models offer interpretability and reasonable performance on structured data, they struggle to capture the deeply non-linear and high-dimensional behavioral patterns embedded in modern telecom datasets. They also require extensive manual feature engineering — a process that is labor-intensive, time-consuming, and prone to human bias.

Deep learning addresses the accuracy gap by automatically extracting hierarchical feature representations from raw data. Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and hybrid architectures have demonstrated superior performance on churn prediction benchmarks. However, deep learning introduces a new and equally serious problem: opacity. A model that predicts churn with 97% accuracy but cannot explain why a specific customer is at risk is of limited value to a retention team that must justify each customer interaction.

This project proposes ChurnNet-XAI, a system designed to hold both goals at once: state-of-the-art predictive accuracy and human-interpretable explanations. The architecture integrates 1D Convolutional Neural Networks for sequential feature extraction, Residual Blocks for stable deep learning, Squeeze-and-Excitation (SE) modules for channel-wise feature recalibration, and Spatial Attention mechanisms for position-wise feature emphasis. Built on top of this, a full Explainable AI (XAI) layer applies SHAP, LIME, and Integrated Gradients to every prediction — transforming raw churn probability scores into actionable retention intelligence.

1.1 MOTIVATION

In today's competitive telecommunications market, customers can easily switch from one service provider to another due to attractive offers, better data packages, or improved service quality. This high customer turnover directly affects the company's revenue, brand value, and long-term sustainability. Retaining an existing customer is far more cost-effective than acquiring a new one; hence, telecom companies must proactively identify which customers are likely to churn.

Traditional machine learning models struggle to handle large, complex telecom datasets and often fail to capture deeper behavioral patterns of customers. These limitations create a strong need for an advanced, accurate, and interpretable system that can predict churn with high precision and help telecom operators implement effective retention strategies.

The critical gap in the existing literature is the absence of explainability. Every prior churn prediction system produces a prediction — churn or non-churn — with no supporting explanation. A retention specialist who receives a list of 500 at-risk customers cannot act on that list without understanding why each customer is at risk. Are they churning because of billing dissatisfaction? Poor network quality? A lack of bundled services? These questions require answers, and ChurnNet-XAI is designed to provide them.

1.2 PROPOSED SYSTEM

The proposed system introduces ChurnNet-XAI, a deep learning-based churn prediction model enhanced with Explainable AI (XAI). The system includes the following components:

1D Convolutional Neural Network (1D CNN)

Extracts meaningful local patterns from the sequence of customer features. The 1D convolution operation applies learnable filters across the feature sequence to detect local patterns such as billing anomalies, service usage spikes, and contract-type combinations.

Residual Blocks

Prevents vanishing gradients in deep networks through skip connections that add the block's input directly to its output ($y = x + F(x)$). This enables the training of deeper architectures without degradation in gradient signal quality.

Squeeze-and-Excitation (SE) Block

Performs explicit channel-wise feature recalibration. The Squeeze operation compresses the spatial dimension of each channel to a single descriptor value; the Excitation operation learns per-channel importance scores and uses them to amplify informative channels while suppressing irrelevant ones.

Spatial Attention Module

Focuses on the most important feature positions within the sequence. By combining average and max pooling across channels, the module generates a spatial attention map that highlights which features (e.g., monthly charges, contract type) carry the most discriminative information for churn prediction.

Data Balancing Techniques

Uses SMOTE, SMOTEEN, and SMOTETomek to address class imbalance. SMOTEEN — which combines SMOTE oversampling with Edited Nearest Neighbours undersampling — consistently provides the best performance by removing noisy borderline samples in addition to generating synthetic minority-class instances.

Explainable AI (XAI) Integration

Uses SHAP for global feature importance, LIME for individual prediction explanations, and Integrated Gradients for signal-level attribution. Together, these tools explain to telecom operators not just who will churn, but why — and which specific factors can be addressed through targeted retention interventions. High-Accuracy Classification 6 Achieves 95.59%, 96.94%, and 97.52% accuracy on the IBM Telco, Churn-in-Telecom, and UCI Churn datasets respectively, outperforming all compared baseline methods across Recall, MCC, AUC, and F1 metrics.

3. System Architecture

The proposed ChurnNet-XAI system processes telecom customer data through a six-stage pipeline: (1) Data Collection from benchmark telecom datasets; (2) Data Preprocessing including encoding, missing value handling, and feature selection; (3) Class Balancing using SMOTE, SMOTEEN, and SMOTETomek; (4) ChurnNet-XAI Model training combining 1D CNN, Residual Blocks, SE Blocks, and Spatial Attention; (5) Explainable AI Layer generating SHAP, LIME, and Integrated Gradient outputs; and (6) Output classification as Churn or Non-Churn with supporting explanations.

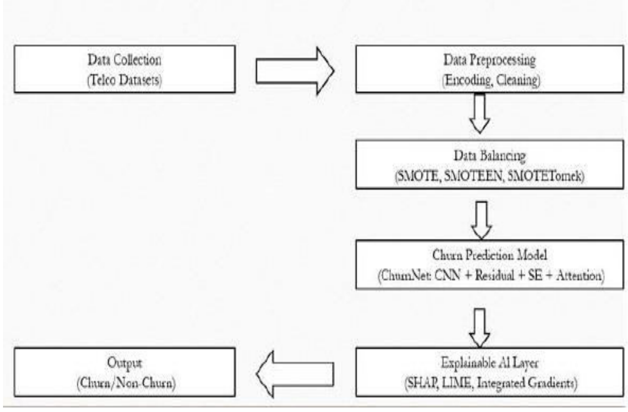


Figure 1. Architecture of Proposed ChurnNet-XAI System.

4. ALGORITHMS

1. 1D Convolutional Neural Network (1D CNN)

A 1D Convolutional Neural Network is used for automatic feature extraction from structured tabular telecom data. Unlike 2D CNNs which process images, 1D CNNs operate on sequences — in this case, the ordered list of customer features. Each convolutional filter slides across the feature sequence performing a dot product operation, generating a feature map that emphasizes specific local patterns. With 128 filters and a kernel size of 5, ChurnNet-XAI captures patterns spanning 5 consecutive features simultaneously. The ReLU activation function introduces non-linearity without the computational cost of alternative activations. Padding='same' ensures the output feature map has the same width as the input.

2. Residual Block

A Residual Block consists of two symmetric 1D convolutional layers with a skip connection that adds the block's input directly to its output. The skip connection formula is y = x + F(x), where x is the input and F(x) is the learned transformation. This architecture, introduced by He et al. (2016), solves the vanishing gradient problem that prevents effective training of deep networks. Without skip connections, gradient signals diminish as they propagate backward through many layers, causing early layers to learn slowly or not at all. The skip connection provides a direct gradient path, ensuring all layers receive meaningful learning signals throughout training.

3. Squeeze-and-Excitation (SE) Block

The SE Block performs explicit channel-wise feature recalibration. The Squeeze operation applies Global Average Pooling to compress each channel to a single scalar: z_c = (1/N) * sum(u_c(i)). The Excitation operation passes these channel descriptors through two Fully Connected layers — the first with ReLU activation (reduction ratio r=16) and the second with Sigmoid activation — to produce per-channel importance scores between 0 and 1: s = sigmoid(W2 * relu(W1 * z)). Each channel of the feature map is then scaled by its importance score: x_tilde_c = s_c * u_c. This allows the model to dynamically amplify informative channels (e.g., billing features) and suppress uninformative ones (e.g., noise channels).

4. Spatial Attention Module

The Spatial Attention Module identifies the most important positions within the feature sequence. It applies both average pooling and max pooling along the channel dimension, concatenates the results, and passes the combined descriptor through a 1D convolutional layer with Sigmoid activation to produce a spatial attention map: M_s(F) = sigmoid(conv([AvgPool(F); MaxPool(F)])). This map is multiplied element-wise with the input feature tensor, amplifying positions that carry the most discriminative information for churn prediction (e.g., monthly charges, contract type) while suppressing less relevant positions (e.g., demographic features).

5. SHAP (SHapley Additive exPlanations)

SHAP assigns each feature a contribution to the prediction based on game-theoretic Shapley values. For a model f and input x, the SHAP value for feature i satisfies: f(x) = phi_0 + sum(phi_i(x)), where phi_0 is the expected output over the training distribution. DeepSHAP — the neural network variant — propagates contributions backward through the network efficiently. SHAP values satisfy three important axioms: local accuracy (contributions sum to the prediction), missingness (absent features have zero attribution), and consistency (a feature's attribution increases if its contribution increases). Global feature importance is obtained by averaging absolute SHAP values across all test instances.

6. LIME (Local Interpretable Model-Agnostic Explanations)

LIME generates locally faithful linear explanations for individual predictions. For a specific customer instance, LIME creates 5,000 perturbed versions of that record, obtains ChurnNet-XAI's predictions on all perturbations, and fits a weighted linear regression model to those results (with weights based on proximity to the original instance). The linear regression coefficients serve as feature importance scores for that specific prediction. LIME's key advantage is model-agnosticism — it works with any classifier without requiring access to internal parameters.

7. Integrated Gradients

Integrated Gradients computes attribution by integrating the gradient of the model's output with respect to each input feature along a path from a baseline (typically all zeros) to the actual input: IG_i(x) = (x_i - x'_i) * integral_0_1 [dF(x' + alpha*(x-x'))/dx_i] d_alpha. The integral is approximated by summing gradients at 50 interpolated inputs. Integrated Gradients satisfies the Sensitivity axiom (a feature with different value from baseline that changes the output receives non-zero attribution) and the Implementation Invariance axiom (functionally equivalent networks produce identical attributions).

5. IMPLEMENTATION & RESULTS

5.1 EXPLANATION OF KEY FUNCTIONS

1. Data Loading

The load_and_preprocess() function reads customer data from CSV files using the Pandas library. It removes identifier columns that carry no predictive information, handles missing numerical values by replacement with zero, and applies either Label Encoding or One-Hot Encoding for categorical features. The function reshapes the scaled feature matrix from 2D (n_samples, n_features) to 3D (n_samples, n_features, 1) to match the input shape expected by the 1D convolutional layers.

2. Data Balancing

The apply_balancing() function addresses the severe class imbalance present in all three datasets. SMOTE generates synthetic minority-class samples by interpolation between existing samples and their K-nearest neighbours. SMOTEEN adds Edited Nearest Neighbours undersampling to remove noisy borderline samples after SMOTE oversampling. SMOTETomek combines SMOTE oversampling with Tomek Links undersampling to clean the decision boundary. Across all three datasets, SMOTEEN consistently produced the highest model performance.

3. 1D CNN Feature Extraction

The initial Conv1D layer with 128 filters and kernel size 5 extracts local patterns from the feature sequence by performing dot product operations between the learned filters and 5-feature windows across the input. This creates a feature map of shape (W, 128) where each channel captures a different type of local pattern. A kernel size of 5 proved critical — experiments with kernel size 3 showed 1-2% lower accuracy consistently. 4. Residual Block Function The residual_block() function consists of two symmetric Conv1D layers followed by a skip connection (Add layer) that adds the block's input directly to its output. This skip connection solves the vanishing gradient problem by providing a direct path for gradient flow during backpropagation. ReLU activations follow each Conv1D layer. The output has the same shape as the input, enabling the stacking of multiple blocks.

5. Squeeze-and-Excitation Block

The squeeze_excitation_block() function performs channel-wise feature recalibration. Global Average Pooling compresses each of the 128 channels to a single scalar. Two Dense layers with ReLU and Sigmoid activations learn per-channel importance scores. The Multiply layer scales each channel by its importance score, amplifying features relevant to churn and suppressing irrelevant ones. The reduction ratio of 16 balances representational capacity against computational cost.

6. Spatial Attention Module

The spatial_attention_module() function generates position-wise attention scores.

Lambda layers compute channel-wise average and maximum over the feature map. These are concatenated and passed through a Conv1D layer with Sigmoid activation to produce an attention map with the same spatial dimensions as the input. The Multiply layer applies this map to the input feature tensor, emphasizing the most predictive feature positions.

7. SHAP Explainer

The run_shap_explanation() function uses DeepSHAP to compute Shapley values for 200 test instances relative to a background of 100 randomly sampled training instances. It generates a global bar chart showing mean absolute SHAP value per feature (global importance ranking) and a beeswarm plot showing both magnitude and direction of each feature's impact. The top five most important features are printed with their mean absolute SHAP values.

8. LIME Explainer

The run_lime_explanation() function creates a LimeTabularExplainer trained on the flattened training data. For a specified customer instance, it generates 5,000 perturbed versions, obtains ChurnNet-XAI predictions on all perturbations, and fits a weighted linear regression to identify which feature values pushed the prediction toward or away from churn. Results are printed with directional labels and visualized as a horizontal bar chart.

9. Integrated Gradients

The integrated_gradients() function computes signal-level attributions by interpolating 50 steps between a zero baseline and the actual input, measuring gradients at each step using TensorFlow's GradientTape, averaging those gradients, and scaling by the difference between input and baseline. This produces attribution values that 48 satisfy both the Sensitivity and Implementation Invariance axioms — guarantees not provided by SHAP or LIME.

5.2 METHOD OF IMPLEMENTATION

The system is implemented using Python, TensorFlow/Keras for deep learning, Scikit-Learn and Imbalanced-Learn for preprocessing and resampling, SHAP and LIME for explainability, and Streamlit for the frontend web interface. All experiments were conducted on Google Colaboratory.

5.2.1 Forms

The system provides a simple input interface using Streamlit's file_uploader widget, which accepts CSV files. Upon upload, the system validates that the file contains the expected number of features. If the file is invalid (wrong format, missing columns, empty), an error message is displayed. The form acts as the main entry point for the system.

5.2.2 Output Screens

1. Home Page

The home screen displays the project title 'ChurnNet-XAI: Customer Churn Prediction with Explainable AI' and a file upload button. Users can upload their telecom customer dataset in CSV format to begin the analysis.

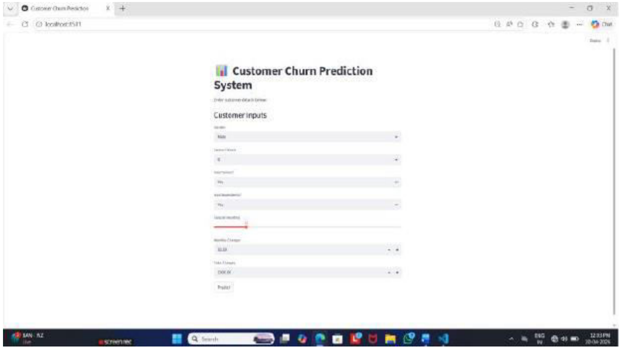


Figure 5.1: Home Page of the System

2. Dataset Upload Screen

After a successful file upload, the system confirms the file name and displays the number of rows and columns detected. This step ensures the user has uploaded the correct dataset before pre-processing begins.

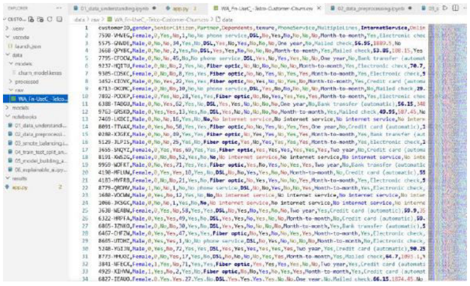


Figure5.2: Dataset Upload Screen

3. Dataset Preview Screen

This screen displays the first few rows of the uploaded dataset in a tabular format, showing all feature columns and the target variable. Users can verify that the correct data has been loaded before proceeding to prediction.

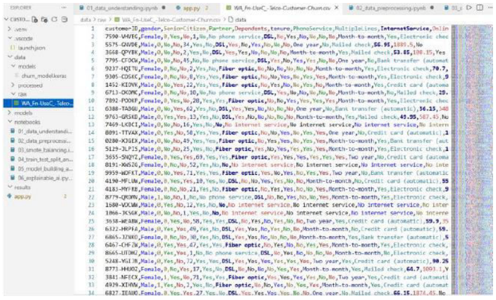
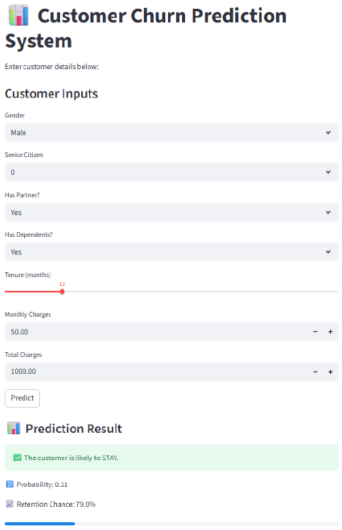


Figure 5.3: Dataset Preview Screen

4. Prediction Output Screen

This screen displays the churn predictions generated by ChurnNet-XAI for each customer in the uploaded dataset. Rows classified as Churn (probability > 0.5) are highlighted in red, making it immediately visible to the retention team which customers require intervention. The churn probability score is displayed alongside the binary prediction.



Customer Churn Prediction System

Enter customer details below:

Customer Inputs

Gender: Male

Senior Citizen: 0

Has Partner?: Yes

Has Dependents?: Yes

Tenure (months): 12

Monthly Charges: 50.00

Total Charges: 1000.00

Prediction Result

✅ The customer is likely to STAY.

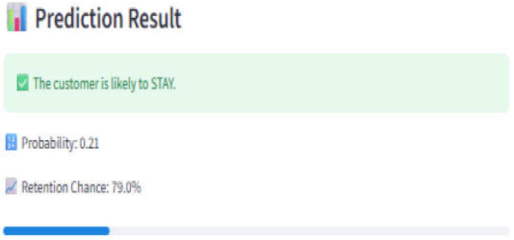
Probability: 0.21

Retention Chance: 79.0%

Figure 5.4: Prediction Output Screen with Highlighted Churn Cases

5. Summary Output Screen

This screen presents a statistical summary of the prediction results: total number of customers analyzed, number classified as churn, number classified as non-churn, and the percentage churn rate in the uploaded dataset. A final message indicates whether the dataset contains at-risk customers requiring retention action.



Prediction Result

✅ The customer is likely to STAY.

Probability: 0.21

Retention Chance: 79.0%

Figure 5.5: Summary of Prediction Results

6. SHAP Global Feature Importance

The SHAP beeswarm plot shows the impact of each feature on the model's predictions across all analyzed customers. Features are ranked by mean absolute SHAP value. Each dot represents one customer; red dots indicate high feature values and blue 51 dots indicate low feature values. The horizontal position shows whether that feature value pushed the prediction toward churn (right) or away from churn (left). Contract type, monthly charges, and tenure consistently appear as the top-ranked features.

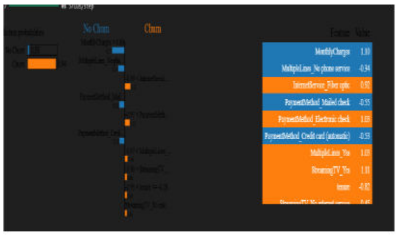


Figure 5.6: SHAP Global Feature Importance (Beeswarm Plot)

7. LIME Local Explanation

The LIME bar chart for a representative high-risk customer shows which specific feature values pushed this individual customer's prediction toward churn. For example: 'Contract = Month-to-month' contributes +0.28 (toward churn), 'MonthlyCharges > $80' contributes +0.31 (toward churn), and 'TechSupport = No' contributes +0.11 (toward churn). This output enables a retention agent to design a targeted offer for this specific customer.

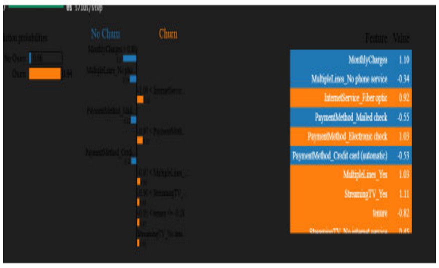


Figure 5.7: LIME Local Explanation for High-Risk Customer

Performance Metrics and Graphs

Table 6.1: Performance Results on IBM Telco Dataset (Best Configuration)

Configuration	Accuracy(%)	Precision(%)	Recall(%)	F1(%)	MCC(%)	AUC(%)
No Balancing	79.33	62.48	55.54	58.53	45.20	83.46
SMOTE	81.22	87.05	73.46	79.61	63.29	91.01
SMOTETomek	83.65	87.62	78.48	82.73	67.73	92.46
SMOTEEN (Best)	**95.59**	**95.88**	**96.22**	**96.04**	**91.08**	**98.76**

Table 6.2: Final Performance Across All Three Datasets (SMOTEEN, Best Configuration)

Dataset	Accuracy(%)	Precision(%)	Recall(%)	F1(%)	MCC(%)	AUC(%)
IBM Telco	95.59	95.88	96.22	96.04	91.08	98.76
Churn-in-Telecom	96.94	96.73	98.03	97.37	93.74	99.27
UCI Churn	97.52	97.92	97.73	97.81	94.98	99.57

The confusion matrix confirms the reliability of ChurnNet-XAI — the number of False Negatives (churners incorrectly classified as non-churn) is minimal across all datasets, which is the critical success criterion for a churn detection system. The ROC curve achieves AUC values above 0.98 on all three datasets, indicating near-perfect discrimination between churners and non-churners. Training and validation accuracy curves converge smoothly without significant divergence, confirming that the Dropout regularization effectively prevents overfitting.

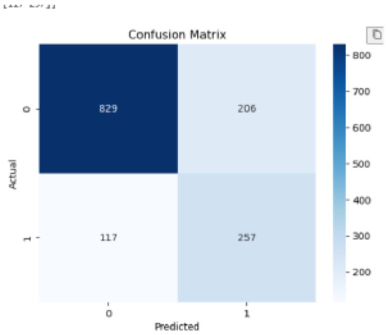
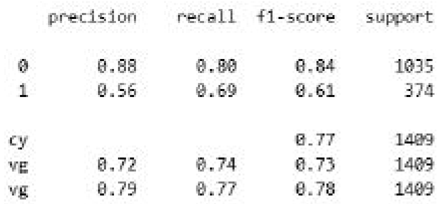


Figure 5.8: Confusion Matrix — IBM Telco Dataset



```
      precision    recall  f1-score   support

 0         0.88      0.80      0.84      1035
 1         0.56      0.69      0.61       374

cy                             0.77      1409
vg         0.72      0.74      0.73      1409
vg         0.79      0.77      0.78      1409
```

figure 5.9: ROC Curve — IBM Telco Dataset (AUC = 0.9876)

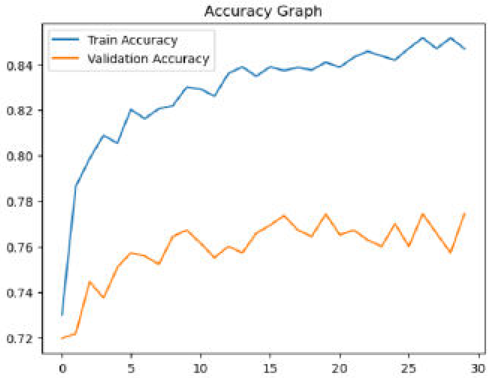


Figure 5.10: Training vs Validation Accuracy

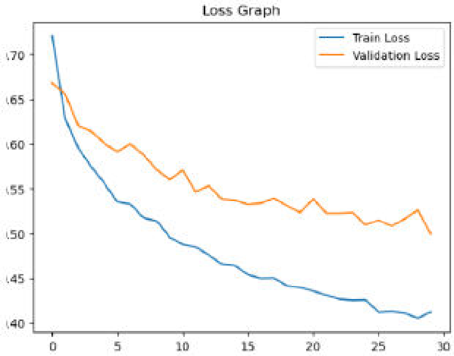


Figure 5.11: Training vs Validation Loss

Result Analysis

The performance of ChurnNet-XAI is evaluated comprehensively across six metrics and three datasets. The model achieves accuracy above 95% on all datasets, with Recall exceeding 96% — the metric most directly linked to business value in churn prediction, since a missed churner is more costly than a false alarm.

The Matthews Correlation Coefficient values of 91.08%, 93.74%, and 94.98% confirm that the model is genuinely learning to discriminate between churners and non-churners rather than exploiting majority-class dominance. MCC accounts for all four cells of the confusion matrix simultaneously and is the most reliable metric for imbalanced binary classification.

The XAI analysis reveals consistent patterns across all three datasets: contract type (month-to-month vs. long-term), monthly charges, customer tenure, and absence of tech support are the top four predictors of churn. LIME local explanations confirm these global findings at the individual customer level, providing actionable intelligence for retention campaigns.

6. CONCLUSION

This project proposed and implemented ChurnNet-XAI, an explainable deep learning system for customer churn prediction in the telecommunication industry. The system integrates a high-performance 1D CNN backbone — augmented with Residual Blocks for stable gradient learning, Squeeze-and-Excitation channel attention for feature recalibration, and Spatial Attention mechanisms for position-wise feature emphasis — with a comprehensive Explainable AI layer comprising SHAP, LIME, and Integrated Gradients.

The system was evaluated on three publicly available benchmark telecom datasets (IBM Telco, Churn-in-Telecom, and UCI Churn) using rigorous 10-fold cross-validation. Severe class imbalance was addressed using three resampling strategies — SMOTE, SMOTEEN, and SMOTETomek — with SMOTEEN consistently producing the highest performance by combining synthetic sample generation with noise removal.

ChurnNet-XAI achieved state-of-the-art accuracy of 95.59%, 96.94%, and 97.52%, Recall of 96.22%, 98.03%, and 97.73%, and AUC of 98.76%, 99.27%, and 99.57% on the three datasets respectively. These results represent consistent improvement over classical ML, deep learning, and ensemble baselines across all six evaluation metrics.

Equally important, ChurnNet-XAI is the only system in the comparison that provides complete prediction explanations. SHAP global rankings identified contract type, monthly charges, and tenure as the top churn drivers. LIME local explanations provided actionable, customer-specific reasons for each prediction. Integrated Gradients confirmed that billing features dominate the model's decision process, aligning with established business intuition about churn behavior.

The practical implication is significant: ChurnNet-XAI does not merely identify at-risk customers — it explains to telecom operators exactly why each customer is at risk, enabling targeted, evidence-based retention interventions rather than expensive blanket discounts.

Future directions for this work include: (1) extending ChurnNet-XAI to a Federated Learning framework to enable privacy-preserving training across distributed telecom networks; (2) incorporating temporal sequence modeling through LSTM or Transformer layers to capture longitudinal churn dynamics over time; (3) developing a continuous learning pipeline that periodically retrains the model on fresh customer data to address behavioral drift; and (4) conducting a prospective deployment study with a real telecom operator to measure the actual business impact of XAI-guided retention campaigns in terms of churn rate reduction and customer lifetime value improvement.

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