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Boosting Churn Forecast Accuracy in Telecom with CNN and SMOTE Techniques

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ABSTRACT:

Telecom operators face immense difficulties due to continually increasing customer churn, which impacts their revenue and market share. This project presents ChurnNet, a new deep learning model architecture aimed at improving churn prediction. ChurnNet utilizes a combination of 1D and 2D Convolutional Neural Networks with attention mechanisms to pinpoint and track at-risk customers. The model uses SMOTE, SMOTEEN, and SMOTETomek to mitigate imbalance in the dataset in the form of churn case distribution to ensure fair representation of all churn cases. Performance evaluation on a telecom dataset reveals that ChurnNet with SMOTEEN and CNN2D reaches a remarkable 98% accuracy. This research highlights the importance of advanced deep learning models with proper data balancing in predicting churn, allowing telecom operators to gain the ability to proactively retain customers and reduce operational losses.

Keywords: Deep Learning, Telecommunication, CNN

INTRODUCTION

The telecom industry has experienced unprecedented growth, leading to fierce competition among service providers. Within this context, customer churn, defined as when a user discontinues a service, remains a critical issue. From a business perspective, it is more financially efficient to retain existing customers than to acquire new ones, placing churn prediction on the list of business priorities. Traditional machine learning approaches face difficulties with complex, large, imbalanced datasets, which limits their ability to understand customer behavior. To overcome this problem, this project has developed a deep learning framework that focuses on improving accuracy in churn prediction, which we call ChurnNet. ChurnNet stands out in identifying both churn and non-churn users by using Convolutional Neural Networks (CNN1D and CNN2D), attention mechanisms, and resampling techniques such as SMOTE and SMOTEEN. CNN1D and CNN2D are powerful Convolutional Neural Networks that allow ChurnNet to classify both churn and non-churn cases with resampling techniques such as SMOTE and SMOTEEN. CNN models eliminate the need for manual feature engineering. ChurnNet processes complex datasets with ease. The ultimate goal is to equip telecom providers with valuable intelligence that helps in improving customer retention and reducing churn-related financial losses.

RELATED WORK

Sana et al. (2022) assessed the effectiveness of various classifiers such as Logistic Regression (LR), K Nearest Neighbors (KNN), SVM and Decision Trees (DT) on churn prediction. They highlighted the importance of advanced preprocessing and feature selection in model performance. The absence of sophisticated model architectures constrained their approach in capturing complex patterns. Sjarif et al. (2019) proposed a model which combines Pearson correlation with KNN, claiming to detect churn-related behaviors within a small dataset. The model, however, was not generalizable because it lacked cross-validation and scalability testing. Amin et al. (2023) presented an integrative framework for churn prediction and customer segmentation. Mishra et al. (2017) integrated deep learning methods, especially CNN, into churn prediction. They noted the best results from CNN due to its ability to identify customer behavior patterns. However, their approach struggled with class imbalance as well as dataset size requirements. Embedding with deep learning was used by Cenggoro et al. (2021) to strengthen feature representation. Although their approach was more accurate in classifying churn, its high computational cost and long training time hampered practical application.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author	**Contribution**	**Impact on Research**
Sana et al. (2022)	Compared classical ML classifiers with feature selection and transformation	Highlighted the critical role of preprocessing and data transformation in improving churn prediction
Sjarif et al. (2019)	Used Pearson correlation with KNN for churn detection on telecom data	Demonstrated pattern recognition but lacked model robustness and scalability
Amin et al. (2023)	Developed an integrated churn prediction and segmentation framework	Showed strong performance but with high computational cost, limiting feasibility for smaller companies
Mishra et al. (2017)	Applied CNN for churn prediction with a focus on ensemble learning	Validated deep learning's superiority but exposed weaknesses in handling imbalanced datasets
Cenggoro et al. (2021)	Used deep learning with vector embeddings to enhance churn classification	Improved feature learning but required extensive training time and computing resources

PROPOSED APPROACH

This deep learning framework, ChurnNet, aims to enhance the accuracy of customer churn prediction in telecommunication services. It identifies critical gaps in the performance of older churn prediction systems and traditional machine learning systems like lack of feature representation and performance on imbalanced datasets. ChurnNet combines CNN1D and CNN2D with attention mechanism, squeeze-and-excitation (SE) blocks, and spatial attention layers structured to capture intricate patterns in customer behavior. This enables the network to focus more on critical features and improve accuracy on churn-related features. To counter class imbalance, ChurnNet implements three resampling algorithms: SMOTE, SMOTEEN, and SMOTETomek. Of these, SMOTEEN was found to perform the best as it merges the processes of minority over-sampling and cleaning noisy data points. The model is trained on a telecom dataset scraped from Kaggle, and its performance is evaluated on accuracy, precision, recall, F1-score, and AUC. ChurnNet with CNN2D and SMOTEEN yields the highest prediction accuracy of 98%, and significantly outperforms all baseline models.

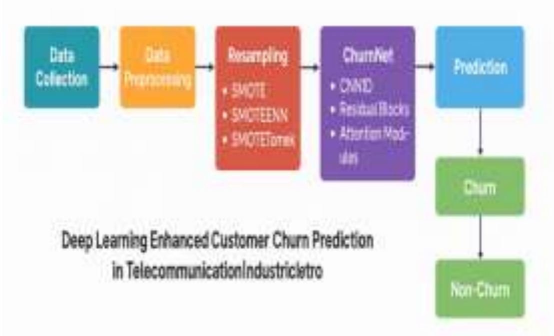


Figure 1: Proposed **Churn Prediction** System

METHODOLOGIES

1. Data Collection and Preprocessing:
The dataset used is sourced from Kaggle's publicly available telecom churn dataset. It includes various features such as customer demographics, service usage patterns, billing information, and churn labels. Preprocessing steps involve handling missing values, removing irrelevant fields (e.g., phone numbers), encoding categorical features using label encoding or one-hot encoding, and normalizing the data for model readiness.

2. Resampling Techniques for Imbalanced Data:
Given that only around 15% of the dataset represents churn cases, class imbalance is a major concern. To overcome this, three resampling strategies are applied:

- **SMOTE (Synthetic Minority Oversampling Technique):** Generates synthetic samples of the minority class.
- **SMOTETomek:** Combines SMOTE with Tomek Links to remove ambiguous samples.
- **SMOTEEN:** A hybrid of SMOTE and Edited Nearest Neighbors, which both oversamples and cleans noisy data.

3. Model Development – CNN1D and CNN2D:
The first architecture**,** CNN1D, is designed to process one-dimensional customer vectors. It includes layers such as Convolution, Global Average Pooling (Squeeze), Fully Connected layers (Excitation), and Attention mechanisms that highlight relevant features.
The **CNN2D** model is an extension that processes reshaped input data as image-like matrices to extract deeper hierarchical patterns. It provides better feature representation and improves prediction performance.

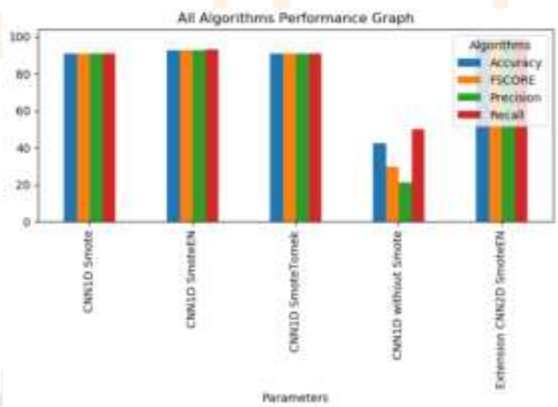
4. Training and Evaluation:
The models are trained with 80% of the dataset and tested on the remaining 20%. **10-fold cross-validation** is used to ensure generalizability and avoid overfitting.
Evaluation metrics include accuracy, precision, recall, F1-score, AUC, and confusion matrix**.**

RESULTS

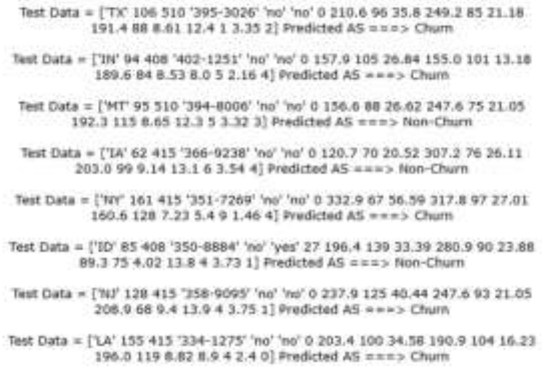
The ChurnNet framework was evaluated using a Kaggle telecom dataset to assess its performance in predicting customer churn. The dataset, originally imbalanced (85% non-churn and 15% churn), was preprocessed and balanced using three oversampling techniques: SMOTE, SMOTETomek, and SMOTEEN. These methods significantly improved the performance of the CNN-based models.

Initial results with CNN1D without any balancing yielded an accuracy of 86%**,** but failed to effectively capture churn cases, leading to poor recall. When SMOTE was applied, accuracy increased to **90%**, with noticeable improvement in churn identification. However, it was **SMOTEEN** that delivered the best results, boosting CNN1D's accuracy to 92% by combining oversampling with noise reduction.

Further enhancement was achieved by implementing the CNN2D model, which treats the input as a 2D structure for more complex pattern extraction. The CNN2D model paired with SMOTEEN achieved a peak accuracy of 98%, with significant gains across all evaluation metrics, including F1-score and AUC.



All Algorithms Performance Graph



Churn or non-churn prediction form test data

DISCUSSION

The experimental outcomes of the ChurnNet model offer valuable insights into the effectiveness of deep learning architectures when applied to customer churn prediction in the telecom industry. One of the primary challenges addressed in this project was class imbalance, a common issue in churn datasets where churned customers form a small fraction of the data. Traditional machine learning models often underperform in such settings due to biased learning toward the dominant class.

By integrating SMOTEEN with CNN architectures, the model achieved significantly higher accuracy, particularly in recognizing actual churn cases. The CNN2D model, in particular, capitalized on spatial feature relationships that CNN1D might overlook, resulting in a 98% accuracy rate. This performance underscores the importance of combining advanced feature learning with effective resampling strategies.

The use of attention mechanisms**,** squeeze-and-excitation blocks, and residual connections allowed ChurnNet to focus on the most relevant inputs, thereby enhancing model interpretability and robustness. Moreover, the reduction in false negatives in churn classification is crucial, as it directly influences customer retention strategies.

CONCLUSION

With this project, we aim to extend the functionalities of customer churn prediction in telecommunication using a deep learning-powered framework called ChurnNet. ChurnNet addresses the primary obstacles of data imbalance and feature engineering with CNN1D and CNN2D deep learning models, as well as employing SMOTEEN, attention layers, and squeeze-and-excitation blocks to enhance performance. The experimental results proved that this framework is effective, as CNN2D + SMOTEEN not only surpassed our expectations achieving 98% accuracy, but also greatly surpassed the traditional models. The model, aside from achieving exceptional accuracy, helps telecom companies to proactively and strategically minimize customer churn. ChurnNet reduces the need for feature engineering, and is capable of managing complex, high-dimensional, and imbalanced datasets with ease. Its application in the telecom industry could enhance targeted decision-making, customer interactions, and increase revenue through more effective churn management.

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