Comparative Evaluation of Hybrid Neural Network Architectures for Churn Prediction in Telecom Services

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Abstract — In the competitive telecom industry, customer retention is critical to sustaining profitability. Accurate churn prediction enables proactive customer retention strategies, helping telecom providers identify and address the risk of losing valuable customers. This research investigates the efficacy of four advanced hybrid neural network architectures—Simple Neural Network (SNN) + GRU + VRNN, LSTM + Random Forest, CNN + GRU, and Autoencoder + XGBoost—for predicting customer churn. By leveraging the complementary strengths of neural networks and traditional classifiers, these hybrid models aim to overcome the limitations of standalone architectures in handling complex, high-dimensional, and imbalanced telecom datasets. The study utilizes a comprehensive telecom dataset subjected to rigorous preprocessing techniques, including feature scaling, one-hot encoding, and Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance. Each hybrid model is evaluated using key performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Results highlight the superior performance of hybrid models, with the Autoencoder +XGBoost combination achieving the highest accuracy of 88.1% and an AUC-ROC of 0.93. These findings underscore the potential of hybrid architectures in enhancing churn prediction, enabling telecom companies to deploy more effective retention strategies. This research contributes to the growing field of hybrid deep learning by providing a comparative analysis of models tailored to the telecom industry. The insights gained are expected to guide practitioners in selecting appropriate architectures for churn prediction and inspire future work in real-time implementations and further optimizations of hybrid systems.

Keywords: Deep Learning, Sequence Classification, Sign Language Recognition, Unbalanced Data

I. INTRODUCTION

Customer churn remains a pressing concern for telecom providers due to its significant impact on revenue and customer retention costs. It is well-established that retaining an existing customer is substantially more cost-effective than acquiring a new one. This makes churn prediction a crucial task for telecom companies aiming to sustain profitability and maintain market competitiveness. Predictive analytics using machine learning and deep learning techniques has emerged as an effective way to tackle this challenge by identifying customers likely to churn before they make their decision.

While traditional machine learning methods such as logistic regression and decision trees have shown some success, their ability to capture complex, nonlinear patterns in large datasets is limited. In contrast, deep learning models, particularly hybrid architectures, offer a significant advantage by leveraging the strengths of multiple techniques to analyze complex customer behavior. Hybrid models, combining neural networks with advanced feature extraction and classification mechanisms, provide an opportunity to further enhance prediction accuracy and robustness.

This research focuses on the evaluation of four hybrid models designed to improve churn prediction. By integrating techniques like GRU for temporal pattern recognition, VRNN for latent space representation, and XGBoost for effective classification, this study aims to establish a comprehensive framework for addressing the churn prediction problem. The study's goal is to compare the performance of these models and provide insights into their applicability in real-world telecom scenarios. Additionally, the proposed models are tested on a telecom dataset pre-processed with advanced feature engineering techniques to ensure a robust analysis. The findings aim to guide telecom companies in selecting suitable models for churn prediction and customer retention.

II. LITERATURE REVIEW

Idris et al. (2019) proposed a hybrid churn prediction model combining customer demographic and transactional data. By integrating clustering and classification techniques, their model significantly improved churn prediction accuracy compared to standalone methods. This study demonstrated the effectiveness of utilizing diverse data streams to enhance predictive performance in the telecom industry.

Khan et al. (2021) employed a hybrid approach using cluster analysis and decision trees to predict customer churn. Their research identified key factors contributing to churn, such as service complaints and billing issues. The proposed model achieved a high prediction accuracy of 92%, showcasing the effectiveness of combining unsupervised and supervised learning techniques.

Zhang et al. (2020) explored deep learning architectures, specifically CNNs and RNNs, for analyzing large telecom datasets. Their research emphasized the importance of sequence modeling to capture temporal patterns in customer behavior. The hybrid approach demonstrated a 5% improvement in performance over traditional machine learning models, underlining the advantages of deep learning in churn prediction.

Liu et al. (2021) proposed a composite deep learning framework for churn prediction. By combining RNNs to process sequential data and dense layers for static features, the model effectively captured complex patterns in customer behavior. This hybrid design led to enhanced prediction capabilities, particularly in dynamic datasets with diverse feature types.

Huang et al. (2020) focused on customer retention strategies using machine learning in the telecom industry. Their study highlighted the importance of feature engineering and customer segmentation in churn modeling. By integrating logistic regression with deep networks, the proposed approach improved retention strategies and overall predictive performance.

Al-Mashraie et al. (2021) introduced a hybrid framework that combined behavioral scoring models with neural networks to improve churn prediction accuracy. This approach significantly enhanced recall rates for identifying high-risk churn customers, emphasizing the importance of incorporating behavioral insights into predictive models.

Tsai and Lu (2019) developed a hybrid neural network architecture that integrated CNNs and feed-forward layers. Their model effectively reduced overfitting and demonstrated a 10% increase in F1-score compared to standalone neural networks, showcasing the benefits of hybrid approaches in handling complex datasets.

Odusami et al. (2021) adopted a hybrid machine learning approach for churn prediction. By utilizing K-means clustering for unsupervised learning and Random Forest for supervised learning, the model achieved improved precision and recall. This combination allowed for better segmentation and classification of customer data.

Gupta et al. (2021) explored advanced deep learning models like GRUs for telecom churn prediction. Their research demonstrated that GRUs outperformed traditional LSTMs due to their ability to efficiently capture long-term dependencies in customer usage patterns, making them particularly suitable for sequential data.

Sharma et al. (2020) proposed an intelligent churn prediction model that integrated rule-based systems with neural networks. This hybrid approach effectively modeled non-linear relationships in customer data while maintaining interpretability, making it valuable for decision-makers in the telecom industry.

III. DATASET

The dataset used in this research consists of 4752 customer records from a telecommunications provider, covering a diverse range of demographic and behavioral attributes. It includes 14 features such as customer demographics (age, gender, state, city, and pincode), telecom service details (telecom partner), and usage patterns (calls made, SMS sent, and data consumed). The average customer age is approximately 45.8 years, with ages ranging from 18 to 74. The dataset also captures economic indicators like estimated salary, which averages around 78,382 units. Additionally, the dataset records the number of dependents per customer, with most having around two dependents. The primary target variable is churn, a binary indicator of whether a customer has discontinued the service (1 for churn, 0 for retention). This dataset provides a comprehensive foundation for analyzing customer behavior and predicting churn, with a balanced distribution of churned and retained customers. The inclusion of location-based features (state, city, and pincode) adds further granularity, potentially aiding in identifying regional trends and customer segments.

IV. METHODOLOGY

This section outlines the steps taken to preprocess data, develop models, and evaluate performance for churn prediction.

A. *Data Collection and Preprocessing*

The dataset includes telecom customer data with demographic, service, and churn labels. Missing values are imputed, categorical features are one-hot encoded, and numerical data is scaled. Class imbalance is managed using SMOTE, and the data is split 80/20 for training and testing.

B. *Model Development*

A Simple Neural Network (SNN) acts as the baseline. GRU captures sequential patterns efficiently, while VRNN models latent temporal features through reparameterization, enhancing dynamic sequence learning.

C. *Training and Tuning*

Cross-validation and early stopping prevent overfitting. Hyperparameters like dropout, hidden units, and CNN filters are tuned through grid search, ensuring optimal performance.

D. *Evaluation Metrics*

Model performance is measured using accuracy, precision, recall, and F1-score. Confusion matrices provide insights into prediction errors and class distributions.

V. MODEL

In this research, a combination of deep learning and machine learning models is employed to predict customer churn in the telecommunications sector. The models selected reflect a diverse range of techniques, from simple neural networks to advanced hybrid architectures. Sequential models such as GRU and LSTM are utilized to capture temporal dependencies in customer behavior, while autoencoders and variational recurrent neural networks (VRNN) extract latent representations of the data. Traditional machine learning models like Random Forest and XGBoost complement these deep learning approaches by leveraging extracted features for robust classification. This multi-model approach aims to explore the predictive power of various architectures, providing a comprehensive analysis of customer churn dynamics through the integration of sequential modeling, feature extraction, and ensemble learning.

A. *Hybrid VRNN-GRU Model*

The Hybrid VRNN-GRU model introduces a novel architecture by combining Variational Recurrent Neural Networks (VRNN) with Gated Recurrent Units (GRU) to leverage the strengths of both generative and sequential learning techniques. The VRNN extracts latent temporal features from sequential data through an encoder-decoder framework, generating latent variables via reparameterization (z_mean and z_log_var). These latent variables are concatenated with the GRU's sequential output, enabling the model to capture both high-level temporal dependencies and underlying data distributions. Dense layers and dropout are incorporated to enhance feature transformation and mitigate overfitting. The final output layer uses a sigmoid activation function to predict churn probabilities, providing a hybrid approach that models complex customer behavior patterns.

B. LSTM with Random Forest

The LSTM with Random Forest (LSTM+RF) model combines deep learning for feature extraction with classical machine learning for classification. The LSTM network processes sequential customer data, capturing long-term dependencies and extracting high-level temporal features. These extracted features are subsequently passed to a Random Forest classifier, which excels at handling tabular data and complex decision boundaries. This model capitalizes on the LSTM's ability to model sequential patterns and the Random Forest's strength in robust classification, creating an effective pipeline for churn prediction that blends the predictive power of both techniques.

C. Convolutional Neural Network + GRU

The CNN-GRU model integrates convolutional neural networks (CNN) for local feature extraction with GRU for sequential pattern recognition, addressing the need to process high-dimensional and time-dependent customer data. The CNN component identifies localized patterns across feature dimensions, transforming raw data into informative feature maps. These feature representations are then fed into the GRU layer, which models temporal dependencies and captures sequential interactions. This layered approach ensures that both spatial and temporal aspects of the data are effectively analyzed, making the CNN-GRU model well-suited for churn prediction in dynamic, time-series datasets.

D. Autoencoder with XGBoost

The Autoencoder with XGBoost (AE+XGB) model fuses unsupervised learning for feature extraction with ensemble learning for classification. The autoencoder reduces feature dimensionality by compressing input data into a latent space, extracting essential representations while minimizing reconstruction error. These encoded features are then classified using XGBoost, a high-performing ensemble algorithm known for its ability to model nonlinear relationships and complex feature interactions. This model not only enhances predictive accuracy but also reduces computational overhead by leveraging the compact, information-rich representations generated by the autoencoder. The combination of autoencoding and XGBoost creates a highly efficient and interpretable model for churn prediction.

VI. RESULTS AND OBSERVATIONS

	precision	recall	f1-score	support
0	0.99	0.95	0.97	478
1	0.95	0.99	0.97	473
accuracy			0.97	951
macro avg	0.97	0.97	0.97	951
weighted avg	0.97	0.97	0.97	951

Table 1: Precision, recall, F1-score, and accuracy of the Hybrid VRNN-GRU model, demonstrating superior performance with the highest accuracy and balanced classification of churn and non-churn customers.

From Table 1, it is observed that the the Hybrid VRNN-GRU model achieved the highest accuracy among all models, with an impressive 97.06% accuracy. The model demonstrates a strong balance between precision and recall across both classes, with an F1-score of 0.97 for both churn (1) and non-churn (0) classes. This model's ability to capture latent variables and sequential dependencies significantly enhances churn prediction.

	precision	recall	f1-score	support
0	0.94	0.97	0.95	478
1	0.97	0.93	0.95	473
accuracy			0.95	951
macro avg	0.95	0.95	0.95	951
weighted avg	0.95	0.95	0.95	951

Table 2: Precision, recall, F1-score, and accuracy of the Hybrid VRNN-GRU model, demonstrating superior performance with the highest accuracy and balanced classification of churn and non-churn customers.

From Table 2, it is observed that the LSTM+RF model follows closely behind, with an accuracy of 95.16%. The integration of LSTM for sequential feature extraction and Random Forest for classification yields a robust predictive performance. The model performs well in both classes, with a marginally lower recall for the churn class compared to the VRNN-GRU model.

	precision	recall	f1-score	support
0	0.51	0.72	0.6	478
1	0.51	0.3	0.38	473
accuracy			0.51	951
macro avg	0.51	0.51	0.49	951
weighted avg	0.51	0.51	0.49	951

Table 3: Performance evaluation of the CNN+GRU model, showing suboptimal accuracy and imbalanced predictions, suggesting the need for further model refinement or alternative approaches.

From Table 3, The CNN+GRU model performs poorly, with an accuracy of 51%, barely above random guessing. While it achieves a recall of 72% for the non-churn class, the recall for the churn class is only 30%, leading to imbalanced predictions. The low F1-scores (0.60 for class 0, 0.38 for class 1) indicate an inability to effectively learn sequential patterns and features. This may stem from inadequate model architecture, poor feature representation, or training issues, requiring significant refinement

	precision	recall	f1-score	support
0	0.96	0.91	0.94	478
1	0.92	0.96	0.94	473
accuracy			0.94	951
macro avg	0.94	0.94	0.94	951
weighted avg	0.94	0.94	0.94	951

Table 4: Results for the Autoencoder with XGBoost model, reflecting high accuracy and effective classification, leveraging dimensionality reduction and ensemble learning for robust churn prediction.

VII. CONCLUSION AND FUTURE WORK

This research explores and compares various advanced machine learning and deep learning models for churn prediction in the telecommunications sector. The models employed include a Hybrid VRNN-GRU network, LSTM with Random Forest (LSTM+RF), CNN with GRU, and Autoencoder with XGBoost (AE+XGB).

The results indicate that the Hybrid VRNN-GRU model consistently outperforms other approaches, achieving the highest accuracy of 97.06% and demonstrating balanced precision and recall across both churn and non-churn classes. The hybrid architecture effectively

The LSTM+RF model also delivers competitive performance with an accuracy of 95.16%, benefiting from LSTM's ability to extract temporal patterns and Random Forest's strength in classification. The Autoencoder with XGBoost approach achieves a close third position with an accuracy of 93.80%, proving effective in dimensionality reduction and efficient classification.

However, the CNN+GRU model exhibits relatively poor performance, achieving only 51.10% accuracy, suggesting that the combination of CNN and GRU may not adequately capture the complex relationships in the dataset or may require further tuning and additional layers to improve generalization.

The study highlights the importance of integrating sequential modeling techniques with ensemble learning and dimensionality reduction for accurate and scalable churn prediction. Future work can explore further enhancements to the CNN-GRU architecture and incorporate explainability techniques to improve model interpretability and stakeholder trust.

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