*Review Article*

Churn Prediction Mechanism Using Deep Learning Methods for High Quality Telecommunication Services – A Review

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ABSTRACT

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| Customer churn remains a critical challenge for the telecommunication industry, directly impacting revenue and customer retention strategies. Traditional churn prediction models based on statistical and machine learning techniques have shown limited adaptability in capturing complex behavioural patterns. Deep learning (DL) methods, particularly recurrent neural networks (RNN), convolutional neural networks (CNN), and transformer-based architectures, have emerged as powerful tools for modelling customer churn by leveraging vast and dynamic datasets. This paper presents a comprehensive review of deep learning-based churn prediction mechanisms in the telecommunication sector, comparing their architectures, feature engineering strategies, and performance metrics. Highlights of recent advances in DL techniques, including attention mechanisms and explainable AI were presented and their implications for improving customer retention strategies were discussed. Finally, key research challenges and future directions in optimizing DL models for real-time and high-quality telecommunication services were also highlighted.  |

*Keywords: [Churn Prediction, Deep Learning, Telecommunication, Customer Retention, Neural Networks, Explainable AI}*

1. INTRODUCTION

Customer churn—the propensity of subscribers to discontinue services within a predefined timeframe—represents a critical operational and financial challenge for telecommunication service providers. In an industry characterised by fierce competition and slim profit margins, churn directly impacts revenue streams, escalates customer acquisition costs (CAC), and undermines long-term customer lifetime value (CLV) [1]. Traditional churn prediction methodologies, including logistic regression, decision trees, and survival analysis, often falter in capturing the non-linear, high-dimensional, and temporally dynamic patterns inherent in modern telecommunication datasets [2]. These conventional techniques rely heavily on handcrafted feature engineering and static assumptions about customer behaviour, rendering them inadequate for modelling complex interactions, such as multi-channel engagement, service usage volatility, and sentiment-driven churn triggers [3].

The advent of deep learning (DL) has revolutionised churn prediction by enabling automated feature extraction from heterogeneous data modalities, including call detail records (CDRs), billing histories, network usage logs, and unstructured customer feedback [4]. Architectures such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks excel in modelling sequential dependencies, making them particularly suited to analysing temporal customer behaviour, such as subscription downgrades, payment delinquencies, or service complaint escalation patterns. For instance, LSTM’s gating mechanisms mitigate vanishing gradient issues, allowing the model to retain long-term dependencies in user activity sequences [5]. More recently, Transformer-based models have demonstrated superior performance in capturing global contextual relationships within customer interaction histories through self-attention mechanisms, which dynamically weigh the significance of features across extended time horizons [6, 7]. Hybrid architectures, such as CNN-LSTM networks, further integrate convolutional layers for spatial feature extraction (such as from service usage heatmaps) with recurrent layers for temporal modelling, enabling multi-modal data fusion [8].

Emerging trends, including Explainable AI (XAI), have critically been examined to address the “black-box” nature of DL models. Techniques like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and attention weight visualisation have been explored for their role in demystifying feature contributions and fostering stakeholder trust [9]. Additionally, we scrutinise barriers to real-world deployment, such as computational latency in processing terabyte-scale CDR datasets, ethical concerns around data privacy (GDPR/CCPA compliance), and the integration of DL pipelines with legacy customer relationship management (CRM) systems.

This paper provides a review of recent advances in deep learning-based churn prediction models in the telecommunication sector, assessing their performance, architectures, and applicability in high-quality service maintenance. Also presented in this article is a robust comparison of deep learning approaches with traditional machine learning techniques along with the discussion of emerging trends such as explainable AI (XAI); equally outlined are challenges that hinder their real-time deployment.

2. bACKGROUND AND REVIEW OF Related LITERATURE

**2.1 Traditional Churn Prediction Approaches**

Traditional churn prediction methodologies predominantly used supervised machine learning (ML) and unsupervised learning techniques, each with distinct strengths and limitations in modelling customer attrition dynamics. A structured technical analysis of these approaches, their operational challenges, and their relevance in historical and modern contexts are provided in the succeeding subsections.

**2.1.1. Supervised Machine Learning Techniques**

1. **Logistic Regression:** Logistic regression (LR) is a parametric statistical model that estimates churn probability by applying a sigmoid function to map linear combinations of input features—such as contract duration and monthly charges—to binary outcomes (churn/non-churn). Praised for its interpretability, computational efficiency, and effectiveness in linearly separable datasets [10], LR remains a foundational tool for risk stratification. However, its reliance on assumptions of feature linearity and independence limits its ability to model complex, non-linear interactions, such as synergies between service usage patterns and demographic variables, thereby reducing its efficacy in capturing nuanced customer behaviour.
2. **Decision Trees:** Decision trees (DTs) are hierarchical, rule-based models that classify churners by recursively partitioning datasets using entropy- or Gini-based criteria, generating interpretable rules such as *“IF monthly usage < 100 MB AND contract month = 1 THEN churn = TRUE.”* Their strengths lie in the intuitive visualization of decision boundaries, inherent robustness to outliers, and capacity to model non-linear relationships within telecom datasets. However, DTs are prone to overfitting when exposed to noisy or sparse data (such as irregular call records) and exhibit instability with minor variations in training data, often requiring ensemble techniques to mitigate these shortcomings [11].
3. **Support Vector Machines:** Support Vector Machines (SVMs) classify churners by optimizing the margin between hyperplanes that separate churn and non-churn instances, using kernel tricks such as radial basis functions to project data into non-linear feature spaces. Their efficacy in high-dimensional environments (such as telecom datasets with hundreds of behavioural metrics) and resilience to overfitting—when paired with regularization techniques—make them robust for complex classification tasks [12]. However, SVMs incur high computational costs when scaling to terabyte-sized telecom datasets and lack inherent probabilistic outputs, necessitating post-hoc calibration (Platt scaling, for example) to estimate churn risk probabilities, which complicates real-time decision-making [13].

**2.1.2. Unsupervised Learning Techniques**

1. **K-Means Clustering:** K-Means clustering partitions customers into distinct groups based on feature similarity (for example, usage patterns and billing cycles) to uncover latent churn-prone segments, operating without reliance on labelled data—a strength particularly valuable for exploratory analysis in early-stage churn studies [14]. Though effective in identifying hidden behavioural patterns, the method necessitates manual interpretation of clusters, struggles with high-dimensional telecom data due to the curse of dimensionality, and inherently assumes spherical cluster shapes, limiting its applicability to complex, non-convex customer behaviour distributions.
2. **Hidden Markov Models (HMMs):** Hidden Markov Models (HMMs) infer latent customer states (for example, “dissatisfied” or “at-risk”) by analysing temporal sequences of interactions, such as call drop frequency or complaint ticket submissions, through probabilistic transitions between hidden states. Their strength lies in capturing temporal dependencies within customer behaviour, enabling dynamic, time-sensitive churn risk assessments. However, HMMs face computational complexity when processing long interaction sequences and depend on manually defined state architectures, which constrain their scalability and adaptability to evolving telecom datasets [15]. A breakdown of the categories of the traditional churn approaches is given in Figure 1.

**2.1.3. Hybrid and Ensemble Approaches**

Traditional machine learning models often suffer from inherent limitations such as high variance (overfitting), high bias (underfitting), or an inability to capture complex feature interactions. To mitigate these weaknesses, hybrid and ensemble frameworks have emerged as powerful techniques that combine multiple models to improve predictive performance, generalization, and robustness. These approaches leverage different learning paradigms, ensuring that individual model shortcomings are compensated by complementary strengths. Below are some widely adopted ensemble and hybrid methodologies:

1. **Random Forests**: Random Forests (RFs) mitigate the high variance and sensitivity of individual Decision Trees (DTs) by constructing an ensemble of decorrelated trees, each trained on a bootstrapped subset of the data (bagging) and a random feature subset at each split [16]. This aggregation—via majority voting or averaging—reduces overfitting, while feature randomization curbs dominance by highly predictive variables, enhancing model diversity. RFs excel in telecom churn prediction by capturing nonlinear interactions (such as between call duration, service complaints, and billing cycles) and delivering stable predictions even with noisy datasets like CDRs. Though highly scalable due to parallelizable training, RFs trade off interpretability for robustness and demand greater computational resources than single-tree.



**Fig. 1. Traditional approaches to churn prediction [7]**

1. **Gradient-Boosted Machines**: Gradient Boosting Machines (GBMs) iteratively build decision trees in sequence, where each subsequent tree corrects the residual errors of its predecessors by minimizing a predefined loss function (for example, log loss for classification) [17]. Unlike parallelized Random Forests, GBMs optimize predictive accuracy through sequential error correction and automatically infer complex feature interactions (such as between call duration peaks and contract expiration dates) without manual engineering. Their flexibility accommodates missing values, categorical variables, and imbalanced datasets via techniques like gradient-based optimization and regularization. In telecom churn prediction, frameworks like extreme gradient-boosted machines (XGBoost) excel at processing sparse CDRs, maintaining robustness against incomplete data (dropped call logs, for example) while outperforming RFs when hyperparameters are meticulously tuned. However, GBMs demand rigorous regularization to prevent overfitting and incur higher computational costs during sequential tree training, trading interpretability for precision in high-stakes churn modelling.
2. **Model Stacking**: Model stacking enhances predictive generalization by combining outputs from diverse base models (example are logistic regression, SVM and decision trees) through a meta-learner, which assigns optimal weights to their predictions. This meta-ensemble approach uses complementary decision boundaries—such as SVMs excelling in high-dimensional feature spaces and logistic regression providing probabilistic interpretability—to synthesize a robust final output. In telecom churn prediction, stacking mitigates single-model biases by integrating, for instance, SVM-based behavioural pattern detection with logistic regression’s risk calibration, followed by a meta-logistic model to refine decisions. While stacking improves stability in imbalanced datasets (sparse churner cohorts, for instance), it introduces computational overhead and requires rigorous cross-validation to prevent the meta-learner from overfitting to base model idiosyncrasies, balancing enhanced accuracy with operational complexity.

**2.1.4. Critical Limitations of Traditional Approaches**

1. **Feature Engineering Burden**: Traditional churn prediction approaches imposed a significant feature engineering burden, necessitating domain expertise to manually craft features—such as *average revenue per user (ARPU) over six months*—that often-lacked generalizability across diverse markets or customer demographics [19]. These handcrafted features, while interpretable, failed to adapt to evolving behavioural patterns or account for contextual nuances (like regional pricing disparities). Furthermore, traditional methods struggled to process unstructured data—including customer service transcripts, social media sentiment, or voice call transcripts—leaving critical behavioural signals (for example, frustration in support interactions) unmodeled [20]. This limitation constrained holistic customer profiling, resulting in incomplete insights into churn triggers and reducing adaptability to dynamic, multimodal telecom datasets.
2. **Temporal and Contextual Blind Spots**: Conventional models exhibited temporal and contextual blind spots, treating customer data as static snapshots (monthly billing cycles, for example) and disregarding temporal dynamics such as gradual usage decay preceding churn [21]. Static frameworks like LR and DTs analysed isolated time points, missing critical longitudinal patterns (like service downgrade trends over quarters). Although HMMs and SVMs capture sequential dependencies, they lack adaptive mechanisms to evolve with shifting customer preferences, such as rapid mobile communication fifth generation (5G) standard adoption or seasonal usage fluctuations [22]. This rigidity led to delayed detection of emerging churn triggers (such as dissatisfaction with legacy network speeds) and misalignment with real-time market dynamics, accentuating the need for architectures capable of continuous temporal-contextual learning.
3. **Scalability and Real-Time Inference**: Traditional methods faced critical scalability and real-time inference challenges, struggling with computational inefficiency when processing terabyte-scale telecom datasets—such as millions of daily CDRs—due to batch-oriented architectures and memory constraints [23]. Static models like LR and DTs incurred prohibitive latency in retraining cycles, hindering real-time updates to churn risk scores (for instance, identifying prepaid users nearing contract expiration for immediate retention offers). This delay between data ingestion and actionable insights often rendered interventions untimely, undermining the agility required in dynamic telecom markets [24]. Coupled with limited support for incremental learning, these bottlenecks constrained the deployment of responsive, high-throughput churn prediction systems, directly impacting customer retention outcomes.
4. **Class Imbalance and Overfitting**: Conventional methods grappled with severe class imbalance (1–5% churn rates), where supervised models disproportionately prioritized non-churners due to skewed training distributions, leading to poor minority-class recall [25]. While techniques like Synthetic Minority Oversampling (SMOTE) artificially augmented churner samples, these ad-hoc fixes often generated unrealistic synthetic instances (for example, interpolated usage patterns) that exacerbated overfitting, particularly in models prone to high variance like decision trees [26]. This imbalance-performance trade-off forced practitioners to prioritize either precision or recall, undermining the reliability of churn risk scores and complicating deployment in high-precision retention campaigns.

**2.1.5. Transition to Deep Learning (DL)**

Traditional ML methods, despite their success, suffer from several limitations, including manual feature engineering, inability to model long-term dependencies, and challenges in handling complex, high-dimensional data. These shortcomings have accelerated the adoption of DL, which has demonstrated superior performance by exploiting automated representation learning, temporal modelling, and scalable architectures [27]. Some strategies DL adopts to overcome these challenges and enhance predictive modelling in the telecom sector as presented as follows:

1. **Automated Feature Learning**: Traditional ML models (like LR, DTs and SVMs) depend on labour-intensive, domain-specific feature engineering, requiring expert-driven curation of attributes like average call duration or service complaint frequency [28]. In contrast, deep neural networks (DNNs), such as Convolutional Neural Networks (CNNs) and Transformers, automate hierarchical feature extraction directly from raw, multimodal telecom data—eliminating manual bias and enabling end-to-end learning [29]. CNNs, for instance, apply 1D convolutions to sequential user activity logs (such as call drops and data usage trends), capturing localized behavioural shifts (for example, abrupt service terminations) without predefined rules. Transformers, through self-attention mechanisms, dynamically weigh interdependencies across heterogeneous inputs—numerical billing records, text-based customer feedback, or geospatial network heatmaps—to synthesize context-aware churn signals [29]. This multimodal fusion, combined with intrinsic noise robustness (for example, handling missing CDR entries through skip connections), allows DNNs to generalize across diverse telecom ecosystems while reducing reliance on brittle, handcrafted feature pipelines.
2. **Temporal Modelling**: Telecom analytics demand robust temporal modelling due to inherently time-dependent data streams—such as billing cycles, call frequency trends, and network session logs—where past behaviours critically influence future outcomes. Traditional ML models (such as feedforward neural networks and SVMs) treat data points as independent snapshots, failing to capture sequential dependencies like gradual service disengagement or prepaid plan expiration patterns. RNNs, particularly, LSTM and Gated Recurrent Units (GRUs), address this gap through gated memory mechanisms that retain historical context over extended periods [30]. For instance, LSTMs model long-term user activity trends (declining data usage over six months, for example) to predict subscription renewal likelihood, while GRUs efficiently detect fraud by analysing abnormal sequences in call records [31]. These architectures excel in scenarios requiring dynamic adaptation to temporal shifts, such as forecasting network congestion during peak hours or identifying at-risk customers through real-time session analytics, outperforming static models by using time-aware feature hierarchies for precision in volatile telecom environments.
3. **Handling Irregular Sequences in Telecom Logs:** Telecom logs often consist of irregular, variable-length sequences—such as sporadic SMS exchanges, fluctuating call durations, and non-uniform billing cycles—that pose challenges for traditional models dependent on fixed-interval inputs [32]. LSTMs and GRUs address these challenges by processing raw, unevenly spaced temporal data directly, without requiring extensive pre-processing steps like padding or aggregation. This preserves the natural irregularity of customer interactions. For example, in CDRs, these architectures effectively model erratic call patterns to detect fraud (like sudden surges in international calls) or evaluate service quality issues (like intermittent call drops) [31]. Similarly, GRUs adapts to irregular mobile data usage patterns, enabling personalized plan recommendations by identifying and learning from consumption spikes. By inherently accommodating temporal irregularities, LSTMs and GRUs provide granular insights into dynamic customer behaviour, avoiding the information loss associated with traditional methods that normalize time-series data.
4. **Detecting Temporal Anomalies in User Behaviour:** Telecom operators face the critical challenge of detecting abrupt behavioural shifts (for example, as sudden engagement drops or anomalous service usage spikes) that signal emerging risks like churn or fraud [33]. Recurrent models like LSTMs and GRUs address this by continuously tracking temporal dependencies in user activity, using their memory cells and gating mechanisms to retain context across extended sequences [34]. For instance, in churn prediction, these models identify subtle precursors (such as declining app logins or dormant SIM activity) by correlating short-term anomalies with long-term engagement trends [34]. Similarly, LSTMs detect billing fraud through irregular payment delays or clustered transaction failures [35], while GRUs monitor Quality of Service (QoS) by flagging deviations from baseline network usage (for example, latency spikes during peak hours) [36]. Through the synthesis of temporal context with adaptive thresholds, these architectures achieve proactive risk mitigation, outperforming static models that overlook the evolutionary nature of customer behaviour in dynamic telecom ecosystems.

Th architecture of traditional neural network is presented in Figure 2 while that of RNN is presented in Figure 3.



**Fig. 2. Neural network architecture [37]**



**Fig. 3. RNN architecture [37]**

**3. DEEP LEARNING ARCHITECTURE FOR CHURN PREDICTION**

**3.2. Recurrent Neural Networks (RNNs)**

RNNs are specialized neural architectures designed to model sequential data (for example, customer interaction histories, time-series data). Their core innovation lies in a hidden state ($h\_{t}$​) that evolves dynamically across time steps, enabling the network to retain contextual information from prior inputs. Mathematically, at each time step $t$, the hidden state is updated as in (1):

 $h\_{t}=σ\left(W\_{h}h\_{t-1}+W\_{x}h\_{x}+b\right)$ (1)

where $W\_{h}$, $W\_{x}$ are weight matrices, $x\_{t}$ is the input, $b$ is a bias term, and $σ$ is a nonlinear activation function (like $\tanh(h)$)

**Limitation:** Despite their sequential modelling capability, vanilla RNNs (simple RNNs) suffer from the vanishing gradient problem, where gradients diminish exponentially during backpropagation through time (BPTT). This inhibits learning of long-term dependencies (an example is a customer’s initial sign-up event influencing churn months later). The issue arises because repeated multiplication of small gradients during BPTT erases critical historical signals, rendering RNNs ineffective for lengthy sequences.

**3.2 Long Short-Term Memory (LSTM) Networks**

LSTMs, introduced by [38], address this limitation through a gated architecture and a dedicated memory cell ($C\_{t}$​). Key components include:

1. Forget Gate ($f\_{t}$): Decides what information to discard from $C\_{t-1}$.
2. Input Gate ($i\_{t}$): Controls how much new information (from candidate cell state $\acute{C}\_{t}$ is added to $C\_{t}$.
3. Output Gate ($o\_{t}$): Regulates the exposure of $C\_{t}$ to the hidden state $h\_{t}$.

The cell state update equation are in (2), (3) and (4):

 $C\_{t}=f\_{t}⨀C\_{t-1}+i\_{t}⨀\acute{C}\_{t}$ (2)

 $\acute{C}\_{t}=\tan(h)\left(C\_{t}\left[h\_{t-1},x\_{t}\right]+b\_{C}\right)$ (3)

 $h\_{t}=o\_{t}⨀tanh\left(C\_{t}\right)$ (4)

where $⨀$ denotes element-wise multiplication. This design allows LSTMs to selectively retain or discard information over arbitrary time intervals, mitigating gradient issues and enabling robust modelling of long-range dependencies.

**3.2.1 Application to Churn Prediction**

In customer churn prediction, LSTMs excel by capturing temporal patterns in interaction sequences (for example, login frequency, purchase history and service complaints). For instance:

1. A gradual decline in usage over months can signal impending churn.
2. Specific events (unresolved support tickets, for example) may have delayed impacts.

Traditional models (like logistic regression and SVMs) often fail here, as they treat inputs as static or ignore temporal order. LSTMs, however, process raw sequential data directly, preserving the chronology critical for accurate predictions. Studies like [39] demonstrate LSTMs outperform traditional methods in accuracy, AUC-ROC, and F1-score, particularly in scenarios with complex, long-term behavioural trends.

**3.2.2 Professional Relevance**

From a business perspective, LSTM-based churn models enable proactive retention strategies. By identifying at-risk customers earlier, firms can deploy targeted interventions (examples are personalized offers and proactive support), reducing customer acquisition costs and improving lifetime value. The model’s ability to handle raw sequential data (instances are clickstreams and transaction logs) also reduces reliance on manual feature engineering, accelerating deployment in real-world systems.

**3.2.3 Trade-offs and Considerations**

Although LSTMs mitigate vanishing gradients, they introduce higher computational complexity due to their gated mechanisms. Techniques like mini-batch training and GPU acceleration are often employed to manage this. Alternatives like GRUs (Gated Recurrent Units) offer simplified architectures but may sacrifice performance on very long sequences. For most customer analytics tasks, LSTMs strike an effective balance between complexity and predictive power.

**3.2. Convolutional Neural Networks (CNNs)**

Although CNNs are primarily used in computer vision, their application in churn prediction involves detecting local spatial correlations in customer behaviour [40]. CNNs extract high-level representations from raw customer data, improving feature extraction efficiency. Recent studies have combined CNNs with LSTMs, achieving state-of-the-art results in telecom churn prediction [41]. Fig. 4 shows a graphical illustration of the CNN architecture.



**Fig. 4. CNN architecture [42]**

**3.3. Transformer Models and Attention Mechanisms**

The Transformer model [43] utilized self-attention mechanisms to dynamically weigh input features based on relevance, making it highly effective for complex customer interactions. Transformers outperform LSTMs in long-range dependency modelling and have been successfully applied to real-time churn prediction in large-scale telecom datasets [44]. A typical architecture of transformer and attention mechanism is shown in Fig. 5.



**Fig. 5. Transformer models and attention mechanisms architecture [45]**

**3.4. Hybrid Deep Learning Approaches**

Hybrid models combining LSTMs, CNNs, and Transformers further enhance churn prediction by exploiting the strengths of each architecture. Graph Neural Networks (GNNs) have also been explored to model customer relationships and network effects in telecom datasets [46].

4. Performance Evaluation and Notable Findings

Table 1 gives a tabulated comparison of different model that has been explored in literature for churn prediction.

**Table 1. Performance comparison of selected models**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Dataset** | **Accuracy (%)** | **F1-Score** | **Notable Findings** |
| Logistic Regression | Telecom Churn Dataset (Kaggle) | 85.2 | 0.78 | Baseline model with limited feature learning |
| Decision Tree | Open Tel Dataset | 87.5 | 0.81 | Good interpretability but overfitting issues |
| LSTM | Telecom-1M Dataset | 92.1 | 0.89 | Strong temporal feature leaning |
| CNN | Telecom-1M Dataset | 91.8 | 0.88 | Effective spatial feature extraction |
| Transformer | Custom Telecom Dataset | 94.5 | 0.91 | Best performance in long-range dependencies |

The comparison revealed that transformer-based models achieved the highest accuracy and F1-score, highlighting their potential for real-time, high-quality churn prediction.

5. Contemporary Challenges and Prospective Research Trajectories

Despite advancements, several challenges remain in deep learning-based churn prediction:

1. Data Imbalance – Telecom churn datasets are typically skewed, requiring techniques like SMOTE or cost-sensitive learning to address class imbalance [47].
2. Explainability – Deep learning models often function as "black boxes"; integrating explainable AI (XAI) can enhance model interpretability [48].
3. Real-Time Inference – Optimizing deep models for low-latency deployment is critical for real-world applications [49].

Future research should explore self-supervised learning, federated learning for privacy-preserving churn prediction, and cross-modal deep learning for integrating diverse telecom data sources.

6. Conclusion

Deep learning has significantly advanced churn prediction in the telecommunication industry, outperforming traditional machine learning techniques in accuracy and feature extraction capabilities. Transformer-based architectures have emerged as the most effective models, offering superior long-range dependency handling and scalability for real-time applications. Addressing challenges in data imbalance, model explainability, and deployment efficiency was suggested to be crucial in fully exploiting deep learning for high-quality customer retention strategies.

Competing interests

The authors declare that no competing interest exist.

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