MACHINE LEARNING FOR TRAFFIC PREDICTION IN MOBILE COMPUTING: TRENDS, CHALLENGES, AND RESEARCH DIRECTIONS

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ABSTRACT

Mobile traffic prediction and call drop reduction remain critical challenges for telecommunications providers, as they directly affect user satisfaction and network efficiency. A call drop, defined as the unexpected termination of a call before either party ends the conversation, often results from network congestion, coverage deficiencies, or system malfunctions. Traditional statistical techniques have shown limited effectiveness in modeling the highly dynamic and complex nature of mobile networks. In contrast, recent research highlights the growing role of machine learning (ML) and data mining methodologies in capturing non-linear patterns, forecasting traffic loads, and improving quality of service (QoS). This review paper synthesizes ten recent studies (2021–2025) that explore models such as decision trees, random forests, gradient boosting, and deep learning architectures including LSTM and CNN-LSTM. Key findings emphasize the advantages of ML in enhancing prediction accuracy, optimizing network resources, and supporting energyefficient operations. However, persistent challenges such as data imbalance, feature selection, model interpretability, and scalability hinder real-time deployment. The review concludes by identifying open research directions, particularly the need for explainable, federated, and hybrid ML approaches that can be seamlessly integrated into 5G and future 6G networks.

KEYWORDS

Mobile networks; Traffic prediction; Call drop reduction; Machine learning; Deep learning; Quality of Service (QoS); Network optimization; Base station coverage; Energy efficiency; 5G/6G

1. INTRODUCTION

1.1. Background

The rapid growth of mobile computing has led to an unprecedented surge in data traffic, fueled by applications such as video streaming, online gaming, cloud services, and the Internet of Things (IoT). This explosive demand places enormous pressure on cellular networks, resulting in persistent challenges including traffic congestion, spectrum scarcity, call drops, and reduced Quality of Service (QoS). Among these, call drops—defined as the sudden termination of a call before completion remain one of the most visible indicators of poor network performance, directly affecting both user satisfaction and operator efficiency (Ashok & Kumari, 2022; Rony, Lopez-Aguilera, & Garcia-Villegas, 2021).

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1.2. Limitations of Traditional Approaches

Historically, statistical and rule-based methods such as queuing models and regression analysis have been used for traffic prediction and anomaly detection. While useful in earlier generations of networks, these methods struggle to address the nonlinear, time-varying, and large-scale behavior of modern cellular systems. They often fail to generalize across diverse traffic patterns and cannot adapt efficiently to dynamic environments (Fauzi, Nordin, Abdullah, &Alobaidy, 2022).

1.3. Rise of Machine Learning in Mobile Networks

Machine learning (ML) has emerged as a transformative approach for tackling these limitations. By leveraging large-scale datasets, ML algorithms can uncover hidden patterns, adapt to changing network conditions, and provide accurate forecasts. Supervised methods such as Decision Trees, Random Forests and Gradient Boosting has been effective for call drop prediction, coverage estimation, and classification tasks (Alekseeva et al., 2021; Fauzi et al., 2022). Deep learning approaches, particularly Long Short-Term Memory (LSTM) networks and CNN-LSTM hybrids, have achieved superior performance in modelingspatio-temporal dependencies in mobile traffic (Jain & Mahant, 2024; Riaz, Güneş, Benli, & Ahmadzai, 2025). Beyond prediction, reinforcement learning has been applied for intelligent spectrum allocation (Rony et al., 2021), while ML-driven frameworks support energy-efficient base station operations (Kolackova, Phan, Jerabek, Andreev, & Hosek, 2025).

1.4. Persistent Challenges

Despite these advances, several challenges hinder widespread deployment. Data imbalance in telecom datasets often skews model performance. The interpretability of deep learning models remains limited, making network operators hesitant to rely on them for critical decision-making. Moreover, real-time implementation in fast-changing mobile environments requires lightweight, scalable, and adaptive solutions (Nashaat, Mohammed, Abdel-Mageid, & Rizk, 2024). As networks evolve toward 5G and 6G, ensuring integration with emerging paradigms like federated learning and edge intelligence is an additional challenge.

2. LITERATURE REVIEW

2.1. Call Drop Reduction

Call drops remain one of the most critical issues in mobile computing, directly affecting user satisfaction. Ashok and Kumari (2022) investigated machine learning approaches for mobile call data analysis, applying Decision Trees and data mining techniques. Their study reported an accuracy of nearly 90% in predicting potential call drop events, demonstrating the effectiveness of ML compared to traditional statistical methods. Similarly, Rony, Lopez-Aguilera, and GarciaVillegas (2021) explored dynamic spectrum allocation strategies based on traffic predictions. Their results showed that MLdriven spectrum-aware allocation improved QoS and reduced interference, indirectly contributing to lower call drop rates.

2.2. Traffic Prediction Models

Accurate traffic forecasting is essential for efficient resource allocation in mobile networks. Alekseeva et al. (2021) compared several ML techniques—including SVM, KNN, Ridge Regression, and Random Forest—on real wireless network data. Their results highlighted that ensemble methods like Random Forest and XGBoost outperformed classical ML models, though scalability issues remained. Nashaat, Mohammed, Abdel-Mageid, and Rizk (2024) proposed a data reduction–based approach for traffic forecasting, integrating models such as Linear Regression, Support Vector Regression, and LightGBM. Their framework enhanced prediction accuracy for LTE-Advanced KPIs, showing the value of preprocessing and dimensionality reduction. Riaz, Güneş, Benli, and Ahmadzai (2025) conducted a comparative analysis using realworld datasets from Afghanistan, evaluating models such as Linear Regression, Random Forest, SVM, XGBoost, LSTM, and GRU. Their findings showed that deep learning models, particularly LSTM, consistently outperformed traditional approaches with the lowest RMSE (688.81), lowest MAPE (37.94%), and highest R^2 (0.592). This study reinforced the growing dominance of deep learning in handling temporal dependencies in network traffic.

2.3. Coverage Prediction

Coverage estimation plays a vital role in ensuring connectivity and reducing call failures. Fauzi, Nordin, Abdullah, and Alobaidy (2022) applied supervised ML algorithms—including Decision Trees, Random Forest, and Gradient Boosting—for mobile network coverage prediction. Their evaluation showed that Random Forest achieved the best accuracy (~94%), demonstrating the potential of ML to assist operators in identifying weak coverage zones and optimizing infrastructure deployment.

2.4.Network Optimization

Beyond traffic forecasting, ML has been leveraged for intelligent network management and optimization. Jain and Mahant (2024) introduced a framework that combined Long Short-Term Memory (LSTM) for traffic prediction with Reinforcement Learning for resource allocation. Their results indicated that LSTM achieved superior performance compared to ARIMA, with $R^2 = 0.92$, MAE = 2.1 Mbps, and RMSE = 3.5 Mbps. The reinforcement learning component further enhanced dynamic allocation, making networks more adaptive. Baradie, Reddy, Lipps, and Schotten (2022) examined ML approaches for traffic prediction in 5G systems, focusing on neural networks for proactive management of virtualized networks. Their findings emphasized the role of ML in enabling predictive, adaptive, and selfmanaging networks.

2.5. Energy Efficiency and Resource Management

Energy consumption is a growing concern in cellular networks, particularly with the rollout of 5G and the anticipated demand of 6G. Kolackova, Phan, Jerabek, Andreev, and Hosek (2025) addressed this issue by developing ML-driven models to optimize baseband unit operations. They applied CNN-LSTM models integrated with reinforcement learning variants (DQN, A2C, Hybrid), concluding that the adaptive fallback DDDQN method achieved the best balance between energy savings, latency, and throughput. Their study demonstrated the dual benefits of ML—both improving network performance and promoting sustainability.

3. Key Findings

The reviewed studies collectively demonstrate the transformative role of machine learning in addressing traffic prediction, call drop reduction, coverage estimation, and network optimization in mobile computing. Ashok and Kumari (2022) showed that Decision Trees and Random Forests could effectively predict call drops with nearly 90% accuracy, highlighting the advantages of ML over conventional statistical approaches. Complementing this, Rony, Lopez-Aguilera, and Garcia-Villegas (2021) applied ML-based traffic forecasting to enable dynamic spectrum allocation in 5G networks, achieving improvements in QoS and reducing interference, thereby indirectly lowering call drop rates. Traffic prediction has been a central focus, with Alekseeva et al. (2021) comparing several algorithms and concluding that ensemble methods such as Random Forest and XGBoost consistently outperform simpler models, though scalability remains a challenge. Yuliana et al. (2024) advanced this line of work by predicting base station traffic and throughput from KPI data, demonstrating that XGBoost achieved the highest performance with R^2 values of 0.976 for traffic and 0.943 for throughput. Similarly, Nashaat et al. (2024) proposed a data reduction– based approach, showing that preprocessing significantly enhances the accuracy of ML models like Linear Regression, SVR, and LightGBM on LTE-Advanced datasets. Deep learning approaches further strengthened predictive capabilities. Riaz, Güneş, Benli, and Ahmadzai (2025) compared multiple models on Afghan LTE datasets, finding that LSTM outperformed traditional methods, achieving the lowest RMSE (688.81), lowest MAPE (37.94%), and highest R^2 (0.592). Jain and Mahant (2024) combined LSTM with reinforcement learning for intelligent network optimization, reporting superior accuracy compared to ARIMA ($R^2 = 0.92$ vs. 0.76) and demonstrating that reinforcement learning enhances resource allocation in dynamic environments.

Beyond prediction, ML has been extended to coverage and energy efficiency. Fauzi, Nordin, Abdullah, and Alobaidy (2022) showed that Random Forest achieved the highest accuracy (~94%) in mobile network coverage prediction, offering practical value for identifying weak coverage zones. Baradie, Reddy, Lipps, and Schotten (2022) reinforced the role of ML in 5G by demonstrating that neural networks enable proactive management of virtualized systems, paving the way for self-managing networks. Finally, Kolackova, Phan, Jerabek, Andreev, and Hosek (2025) highlighted the sustainability dimension, showing that CNN-LSTM models integrated with reinforcement learning, particularly adaptive fallback DDDQN, achieved the best balance between energy savings, latency, and throughput. outperforms traditional methods in traffic prediction and network optimization. They also emphasize emerging directions such as reinforcement learning, energy efficiency, and coverage optimization, while pointing to ongoing challenges in scalability, real-time deployment, and model interpretability.

Table 1: Summary of Recent Studies on Machine Learning for Traffic Prediction and Network Optimization (2021–2025)

No.	Author(s)	Year	Problem	Model Used	Accuracy / Results
1	Rony, Lopez-Aguilera & Garcia-Villegas	2021	Dynamic spectrum allocation in 5G	ML-based traffic prediction for spectrum aware allocation	Improved QoS and reduced interference by matching predicted vs. real throughput
2	Alekseeva et al.	2021	Comparison of ML models for real wireless traffic prediction	SVM, KNN, Ridge Regression, Random Forest	RF and XGBoost outperformed; scalability challenges noted
3	Ashok & Kumari	2022	Mobile call data analysis for reducing call drops	Decision Tree, Data Mining methods	Accuracy ≈ 90% for call drop classification
4	Baradie, Reddy, Lipps & Schotten	2022	Managing 5G with ML-based traffic prediction	Neural Networks (timeseries)	Effective for virtualized 5G systems; supports proactive management
5	Fauzi, Nordin, Abdullah &Alobaidy	2022	Mobile network coverage prediction	Decision Tree, RF, Gradient Boosting	RF achieved highest accuracy (~94%)
6	Yuliana et al.	2024	Base station traffic & throughput prediction (KPI analysis)	KNN, Random Forest, XGBoost	**XGBoost best**: Traffic prediction $R^2 = 0.976$, Throughput $R^2 = 0.943$
7	Nashaat et al.	2024	Cellular traffic prediction using data reduction	LR, SVR, Decision Tree, LGBM	Aggregated ML framework improved accuracy on LTE-A KPIs
8	Jain & Mahant	2024	Intelligent dynamic network optimization	LSTM (traffic prediction), Reinforcement Learning (resource allocation)	**LSTM**: MAE = 2.1 Mbps, RMSE = 3.5 Mbps, $R^2 = 0.92$ (better than ARIMA, $R^2 = 0.76$)
9	Kolackova et al.	2025	Energy savings in cellular baseband units	CNN-LSTM + Reinforcement Learning (DQN, A2C, Hybrid)	Adaptive fallback DDDQN achieved best trade-off between energy, latency, throughput
10	Riaz, Güneş, Benli, & Ahmadzai	2025	Comparative ML models for cellular load prediction (Afghanistan dataset)	LR, RF, SVM, XGBoost, LSTM, GRU	**LSTM best**: RMSE = 688.81, MAPE = 37.94%, $R^2 = 0.592$

4. CHALLENGES AND LIMITATIONS

4.1. Data Quality and Imbalance

A recurring challenge in ML-based traffic prediction and call drop reduction is the imbalance in telecom datasets. Since call drops occur less frequently compared to normal traffic events, datasets tend to be skewed, which can bias models toward predicting the majority class. This imbalance reduces sensitivity in detecting rare but critical events like call failures (Ashok & Kumari, 2022). Additionally, datasets are often noisy, incomplete, or proprietary, which complicates benchmarking across different networks and limits reproducibility (Nashaat et al., 2024).

4.2. Scalability and Computational Complexity

Many ML techniques show strong results in controlled experiments but struggle when scaled to large, real-world networks. Ensemble methods such as Random Forest and XGBoost have proven effective (Alekseeva et al., 2021; Yuliana et al., 2024), but their computational cost grows with dataset size. Deep learning models such as LSTM and CNN-LSTM require significant processing power and memory, which may not be feasible in latency-sensitive mobile environments (Riaz, Güneş, Benli, &Ahmadzai, 2025; Kolackova et. al., 2025).

4.3. Lack of Interpretability

Although deep learning models achieve higher accuracy, they often function as ―black boxes.‖ Network operators require transparency to trust model outputs, especially for critical tasks such as call drop prediction, spectrum allocation, and QoS optimization. The limited interpretability of complex models like LSTM and CNN-LSTM remains a significant barrier to practical adoption (Jain & Mahant, 2024).

4.4. Real-Time Deployment Challenges

Most reviewed studies reported promising results in offline or simulation-based environments. However, real-time mobile networks demand low-latency, adaptive, and lightweight ML models that can respond to rapidly changing conditions. Models that perform well offline often fail to meet the timing and efficiency requirements of live 5G deployments (Rony et al., 2021). Bridging this gap between research and practice is a key challenge.

4.5. Integration with Emerging Architectures

The shift towards 5G and 6G architectures introduces new challenges in integrating ML solutions into distributed, software-defined, and virtualized environments. Future mobile networks rely on paradigms such as edge computing, network slicing, and federated learning, but most existing studies have yet to address compatibility with these frameworks (Baradie et al., 2022; Fauzi et al., 2022). Without seamless integration, ML models may remain isolated research prototypes rather than scalable operational tools.

5. FUTURE RESEARCH DIRECTIONS

5.1. Improved Data Collection and Balancing

Future studies should focus on building balanced and representative datasets for call drop and traffic prediction tasks. Techniques such as synthetic data generation, oversampling (SMOTE), and anomaly detection frameworks could mitigate class imbalance. Collaboration between telecom operators and researchers will also be essential to create standardized benchmark datasets that improve reproducibility and allow fair model comparisons (Nashaat et al., 2024).

5.1.1. Scalable and Lightweight Models

As mobile networks generate massive amounts of data, there is a need for computationally efficient algorithms. Research should explore lightweight deep learning architectures, pruning, quantization, and knowledge distillation to reduce model size and latency. Additionally, online and incremental learning methods can enable models to adapt continuously to streaming traffic data without retraining from scratch (Riaz et al., 2025).

5.2. Explainable and Trustworthy AI

To overcome the ―black box‖ problem of deep learning, future work should emphasize explainable AI (XAI) approaches. Models must provide interpretable outputs so that network operators can understand and validate predictions before acting on them. Visual analytics, feature attribution methods (e.g., SHAP, LIME), and rule-based hybrid models can make ML decisions more transparent (Jain & Mahant, 2024).

5.3. Real-Time Deployment Frameworks

Bridging the gap between simulation and operational environments requires real-time ML deployment strategies. Edge computing and fog architectures offer promising avenues by enabling models to run closer to data sources with reduced latency. Research should prioritize adaptive, low-latency models capable of making rapid predictions for dynamic environments like 5G and future 6G networks (Rony et al., 2021). **5.5 Integration with 5G/6G Architectures** As networks evolve, ML research must align with emerging 5G and 6G paradigms, including network slicing, software-defined networking (SDN), and cloud-native architectures. Future work should investigate how federated learning can train models collaboratively across distributed devices while ensuring privacy and scalability. This integration will enable ML models to move from isolated prototypes to fully embedded tools within next-generation mobile infrastructures (Baradie et al., 2022; Kolackova et al., 2025).

6. CONCLUSION

Mobile computing networks face persistent challenges such as traffic congestion, call drops, and limited Quality of Service (QoS). Traditional statistical approaches often fail to capture the dynamic behavior of these networks, whereas machine learning techniques offer more accurate and adaptive solutions. This review of ten recent studies (2021–2025), shows that ensemble methods like Random Forest and XGBoost, along with deep learning models such as LSTM, consistently improve traffic prediction and call drop analysis. Reinforcement learning and hybrid approaches further contribute to spectrum optimization and energy-efficient operations. However, challenges remain in dataset imbalance, model interpretability, scalability, and real-time deployment, as well as integration with emerging 5G/6G architectures. Future research should focus on explainable, lightweight, and scalable ML frameworks, supported by federated and edge learning, to enable practical and sustainable adoption in next-generation networks.

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