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Improving Traffic Forecasting Accuracy in Mobile Networks Through Machine Learning-Based Classification Techniques

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Abstract

The cellular network has developed over time from offering rudimentary wireless and mobile phone service to a sophisticated system that offers phone service, Internet access, and interoperability with other technologies (such as Wi-Fi), all while ensuring a flawless user experience. This study presents a machine learning model to forecast mobile network traffic using a real-world Kaggle Mobile Phone Activity dataset, which includes a week's worth of combined CDRs from Milan and Trentino. The data underwent a rigorous preparation process that includes addressing missing values, feature engineering, and minmax normalization before being split into training and test sets. The Random Forest classification model was constructed and tested based on the standard metrics, with the high accuracy of 98.79, a good precision performance, recalls performance, and F1-score performance. The reliability of the model to differentiate the pattern of traffic is also supported by ROC and confusion matrix analysis. The comparative analysis reveals that the proposed Random Forest model performs better than the baseline model of MLP, which exhibits a high degree of robustness and prediction. Altogether, the research provides a useful and efficient framework of improving traffic forecasting and contributing to improved management of resources within the mobile network setting.

Keywords: *Internet Traffic Forecasting, Mobile Networks, LTE Dataset, Network Management, Time Series Modeling, Mobile Traffic Volume, Short-Term Forecasting.*

I. Introduction

Network traffic forecasting is one of the activities that employs machine learning techniques for efficient network administration. This activity tries to manage user demands, minimize service disruptions, monitor user behavior in applications, and detect any issues before they arise [1]. A base station uses traffic predictions for intelligent power use. This issue is examined using base station sleeping, mobile edge computing, network slicing, and extra power during periods of high demand. Both short-term and long-term forecasts are used for traffic, although occasionally medium-term forecasting is also required.

Forecasting the amount of internet traffic is one of the most crucial duties in the proactive administration of contemporary telecommunications networks. Enhancing traffic demand forecasting's precision and effectiveness can aid ISPs in creating sensible business plans and boosting the sector's financial gains. Additionally, very accurate forecasting findings can be useful for advanced network design, route planning, both immediate and long-term business capacity planning, and improved resource management. To put it another way, an accurate traffic prediction system may help ISPs manage their networks in advance and guarantee improved network quality of experience (QoS) [2].

Regardless of their location or time, mobile networks enable users to stay connected at all times, particularly while they are outside. The availability of mobile connection services is still lacking, despite the advancements made in hardware and software development [3]. The antennas in certain places are too short to offer complete signal coverage, and the cellular phone companies' network has not yet been fully extended. Furthermore, future communication networks need to manage the restricted spectrum in order to accommodate the massive rise in heterogeneous wireless devices. In this regard, efforts are being undertaken to address the spectrum's coexistence, increase understanding of it, strengthen scheme authentication to enhance spectrum management and monitoring, and enable secure communications, among other things.

Mobile network traces offer a multitude of information on the network and user activity. However, modeling and analyzing network traces is a difficult procedure. Particularly in the case of extremely congested networks, the unique insights gleaned from the network traffic analysis are extremely beneficial to both network operators and network customers [4]. The network operators can split the network coverage area into several sub-regions if the traffic patterns in cellular networks are effectively predicted and projected. Consequently, traffic patterns may be used to assign network resources to sub-regions. Mobile customers would benefit from such traffic modeling in terms of higher service quality [5]. Additionally, network operators would benefit from network traffic optimization when creating effective operating plans.

Machine learning (ML) is a kind of automated learning technique that finds hidden patterns in data to extract knowledge. The patterns found are utilized to forecast various problems in many sectors by extrapolation, streamlining, or automation [6]. The understanding that mobile cellular networks have become into enormous data producers and carriers is what led to the application of ML in cellular networks [7]. ML can examine these data to address issues. Despite deep learning's (DL) application to network security is relatively new, the academic community has given the issue a lot of attention because of DL's strong auto-learning capabilities [8][9]. Furthermore, the development and growing accessibility of GPU-processors greatly aid in speeding up matrix computations and large-scale mathematical computations, hence immediately bolstering the viability of DL-based methods. In general, there are many types of deep learning for malicious traffic identification that rely mostly on the integrated network model.

A. Motivation and Contribution of Paper

The dynamism of mobile network traffic is very difficult to predict because user requirements are highly dynamic and fast-changing. Conventional means are unable to record the intricate trends, which results in overcrowding and poor service delivery. The motivation behind this research is afforded by the need to have an effective, evidence-based methodology that can help in the proactive management of networks, efficient utilization of resources and enhance user experience. Machine learning provides the potential to discover the hidden patterns in the large-scale network data, allowing predictions more accurate and assist an operator plan and optimize the performance. The following summarizes this study's primary contributions:

- Obtained and used a real-life mobile phone activity data set on Kaggle which offers a practical base on which to base traffic prediction studies.
- Performed comprehensive preprocessing, such as the processing of missing data, normalization, and feature engineering, to enhance data quality and readiness for analysis.
- Built a predictive model based on the random forest that is specific to the representation of intricate mobile network traffic patterns.
- To evaluate the model's performance, a comprehensive performance evaluation based on precision, recall, F1-score, accuracy, and ROC metrics was developed.

B. Novelty & Justification of the Study

The research is explained by the growing need to have precise forecasting of mobile network traffic to maximize traffic performance, control traffic jams, and improve user experience. The complexity of contemporary traffic patterns is another weakness of traditional methods, as machine learning is more powerful. The novelty of the study is that it contains a customized implementation of the framework based on the use of the Random Forest, applied to real-life Kaggle data, which is supported by the detailed preprocessing, feature engineering, and evaluation. This method is more efficient in capturing complex spatial and temporal behavior which means that it creates a model that is more reliable and practical in managing any mobile network

C. Structure of paper

The paper is organized as follows: Section II provides an overview of the body of research on mobile network traffic forecasting. Section III outlines the proposed methodology outlining the dataset, model implementation, and techniques. In section IV, experimental results are described, and the main conclusions are given. Finally, Section V concludes the study by outlining its shortcomings and suggesting avenues for further research.

II. Literature Review

This literature review presents an in-depth analysis of recent studies on mobile network traffic forecasting. Table I offers a consolidated overview of these works, highlighting the methodologies employed, performance outcomes, major findings, noted limitations, and suggested directions for future research.

Wang, Wang and Zhou (2019) elucidate the reasons why the traditional model-based paradigm, which has been shown to be beneficial in pre-5G networks, may be less effective or perhaps less feasible in mobile networks like 5G and beyond. Next, describe how the data-driven paradigm may develop into a viable solution by utilizing cutting-edge machine learning techniques. Finally, provide a typical application of the data-driven paradigm, namely proactive load balancing, where cell designs are modified beforehand using online learning to prevent burst congestion brought on by abrupt changes in traffic [10].

Sheluhin et al. (2019) develop data sets with certain attributes (such as background traffic or the quantity of specific application flows); Assign network traffic packets to streams so that, at user request, new flows, excluding repetitions can be added to the previously constructed data set. An application was created that uses the application programming interface to create virtual private networks, gathers network traffic packets, determines the originating application, and transmits them via HTTP to server software in order to gather traffic from Android-powered mobile devices. Traffic from eighteen primary apps was entered into the database using client and server software. 6,989,991 packets and 71,667 streams were received during the data collection [11].

Kulkarni (2018) Smartphones are widely utilized for a variety of purposes, such as shopping, banking, and knowledge browsing. Everybody has a cell phone in their pocket that contains private or sensitive data about specific users. Sending and receiving requests causes a significant amount of network traffic when users engage with mobile apps. An attacker may be able to access private information by analyzing generated network traffic [12].

Troia et al. (2018) concentrate on deep learning techniques to forecast traffic matrices so that they may proactively improve optical backbone network resource allocations. In the past several years, recurrent neural networks (RNNs), which are made to solve sequence prediction issues, have shown impressive results in tasks including handwriting identification, speech recognition, and time series data prediction. A specific kind of RNN with exceptional accuracy (< 7.4 of mean absolute error) called Gated Recurrent Units (GRU) was studied. The forecasts were then used to an optical network's proactive and dynamic resource allocation. It is possible to predict a 66.3% decrease in the network's available capacity by comparing the numerical results of static vs. dynamic allocation based on forecasts, which would help manage unforeseen traffic surges [13].

Malik et al. (2017) offer a technique for verifying the kind of device via network activity analysis. This study can identify mobile operating systems (OS) using both active and passive network traffic, which makes it comparable to techniques and tools like nMap or xProbe. According to the three main mobile operating system vendors (Android, iOS, and Microsoft), in order to save battery life, they should down-throttle the network response of some network traffic that is sent to them (like ICMP pings) or requested by them (like streaming TCP/IP). This strategy is based on repeatable experiments [14].

Alvizu et al. (2017) A software-defined mobile carrier network can benefit from the application of a matheuristic for dynamic optical routing. It employs machine learning to forecast changes in tidal traffic in a mobile metro-core network in order to handle offline mixed-integer linear programming scenarios of an optical routing (and wavelength) assignment optimization issue. Near-optimal online routing choices are favored by the ideal outcomes. The online approach's effectiveness is demonstrated by the results, which almost perfectly replicate the behavior of a network reconfiguring optical routing while resolving an optimization problem and generating a precise, oracle-like traffic estimate [15].

Huang, Chiang and Li (2017) present a deep learning network-based multitask learning architecture for mobile traffic forecasting. Recurrent neural networks (RNNs), three-dimensional convolutional neural networks (3D CNNs), and CNN-RNNs—a hybrid of CNN and RNN are some of the cutting-edge deep learning models examined. The tests suggest that CNN and RNN can extract temporal and geographic traffic features, respectively. CNN-RNN is a dependable model that leads all tasks with 70–80% predicting accuracy when compared to deep or non-deep learning techniques [16].

TABLE I: SUMMARY OF LITERATURE OVERVIEW AND REVIEW ON TRAFFIC FORECASTING IN MOBILE NETWORKS.

Author(s)	Method	Dataset	Findings	Challenges	Future Strategy
Wang, Wang & Zhou (2019)	Data-driven paradigm using ML; Online learning for proactive load balancing	Not specific general mobile network traffic scenarios in 5G	Model-based paradigms fail in 5G; ML-based dynamic adaptation improves congestion control; online learning adjusts cell configurations in advance	Rapid, unpredictable traffic patterns; difficulty of real-time adaptation; scalability across heterogeneous 5G environments	Use reinforcement learning for autonomous network control; integrate federated learning for distributed prediction; deploy real-time self-optimizing networks
Sheluhin et al. (2019)	Android VPN-based traffic collection; Stream grouping; Dataset generation tool	Traffic collected from 18 Android applications (71,667 streams, ~7M packets)	Developed system collects, labels, and streams traffic to server; enables dataset creation with customizable flows	Limited to Android OS; relatively small dataset; privacy and identification challenges; lacks sophisticated attack traffic	Expand dataset across multiple platforms (iOS/Windows); use GANs to generate synthetic traffic; implement privacy-preserving traffic analytics; automate labeling using ML
Kulkarni (2018)	Network traffic analysis to detect privacy leakage risks	General smartphone-generated network traffic	Sensitive data can be exposed through mobile app network traffic; attackers can analyze requests/responses to infer private user information	Inadequate encryption; ease of traffic interception; user unawareness; insecure app design	Build ML-based mobile IDS; enforce stronger cryptographic protocols; develop secure-by-design mobile app frameworks; user-centric privacy solutions
Troia et al. (2018)	GRU-based RNN for traffic matrix prediction; Dynamic optical resource allocation	Optical backbone network traffic matrices	GRU achieves MAE < 7.4; predictive dynamic resource allocation saves 66.3% capacity; handles unexpected traffic peaks	Requires high-volume training data; limited generalization to volatile traffic; accuracy loss in long-term forecasts	Introduce attention-based RNNs or Transformer models; integrate RL for real-time routing; test on large-scale networks
Malik et al. (2017)	Device type verification using passive & active network traffic profiling	Traffic from mobile devices (Android, iOS, Microsoft)	OSes throttle network response differently; fingerprinting possible via ICMP/TCP behaviour; identifies device types reliably	Inconsistent throttling patterns; device variation; privacy concerns in OS fingerprinting	Expand classification to model-level identification; develop obfuscation-resilient fingerprinting; create privacy-preserving

					verification frameworks
Alvizu et al. (2017)	ML-based traffic prediction + matheuristic for optical routing	Mobile metro-core network traffic	Achieves near-optimal routing performance comparable to oracle predictions; predicts tidal traffic effectively	High computation for offline optimization; dependency on prediction accuracy; difficulty reacting to sudden anomalies	Use deep learning for anomaly-aware predictions; test in real SDN environments; develop online, low-complexity routing solvers
Huang, Chiang & Li (2017)	Deep learning multitask model (CNN, RNN, 3D-CNN, CNN-RNN)	Spatiotemporal mobile traffic data	CNN extracts spatial features; RNN captures temporal patterns; CNN-RNN achieves 70–80% accuracy	High computational cost; harder to model sparse/bursty traffic; scalability issues for large regions	Explore transformer-based forecasting; optimize models for edge deployment; apply transfer learning across cities

III. Research Methodology

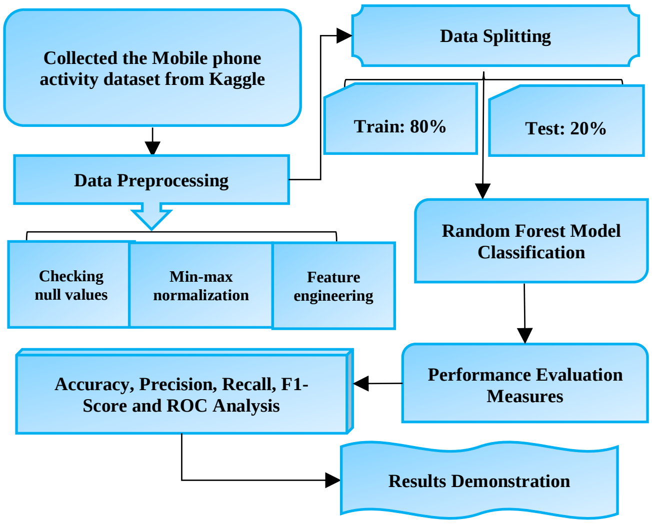

Fig 1: Flowchart diagram of the Traffic Forecasting in Mobile Networks.

The mobile network traffic forecasting is fundamental to effective resource allocation, congestion control, and to the improvement of user experience. The study's objective is to create a dependable and efficient model for predicting mobile network traffic using actual activity data. Through the employment of data preprocessing methods and the use of a Random Forest classifier, the research aims to define the traffic patterns correctly and measure the work of the models using conventional classification measures. Finally, it is aimed at proving a sound method that allow improving traffic predictability and contributing to improved decision-making in mobile network management. Figure 1 shows the flow of the study.

The steps as shown in the flowchart are explained in detail and in a step-by-step manner as follows:

A. Data Collection

The study made use of the Kaggle mobile phone activity dataset, which consists of a week's worth of Call Details Records (CDRs) from the Italian province of Trentino and the city of Milan. It is composed of several CSV files that denote hourly mobile activity throughout a week (7 days) and the related spatial grid files. The EDA for this dataset is shown below:

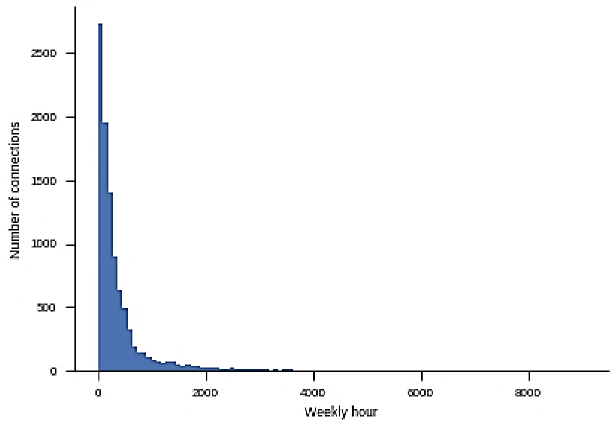

Fig 2: Activity of the number of connections vs. weekly hours.

Figure 2 indicates that the distribution was highly skewed to the right, with the mobile network connection highest on the first hours of a week, and then sharply declining to the right with a long tail, which indicates continuous reducing activities with time.

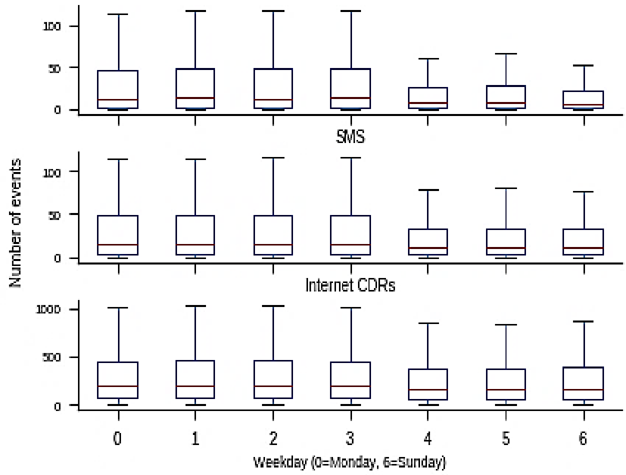

Fig 2: Boxplot grouped by weekday calls.

Figure 3 indicates that SMS activity is relatively low and stable throughout the weekdays whereas Internet CDRs are relatively high and greater and less stable meaning more consistent messaging behavior but variable and greater data usage throughout the week.

B. Data Preparation

The ML models made many preprocessing changes to the training dataset in order to increase training accuracy and decrease training loss.

1) Checking Null Values

It is the process of determining any gaps in timestamps, cell IDs or measures of activity (SMS, calls, internet). Since the data is summarized using grid cell and hour, a null could signify an hour or area that no activity or data are recorded.

2) Min-Max Normalization

The MinMax scaling is used to normalize the data and the data is converted to a range between 0 and 1. Equation (1) may be used to represent the max–min mapping approach:

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

3) Feature Engineering

This entails the creation of new informative variables by the aggregated data of mobile activity to increase analysis and modelling. This can be time-related (hour of the day, weekday/weekend), the intensity of traffic in terms of number of activities per grid cell, usage proportions or spatial summaries reflecting an average behavior in grid cells. Such derived features contribute to the exposure of usage patterns and enhance the comprehension of both the dynamics of a temporal and a spatial network.

C. Data Splitting

This dataset was split 80:20, with 80% going toward model construction and the remaining 20% going toward testing the model to determine how well it performs with previously unseen data.

A. Model Classification

A random forest (RF) is made up of many decision trees and was first presented in 2001. The foundation learner should be "good but different," which implies that each learner should be distinct and have a comparatively high recognition rate, according to the theory behind ensemble learning. However, selecting only one option predetermines the number of decision trees [17]. Decision trees are created at random, and an integrated voting process determines the outcome. Decision trees may not differ much from one another when several single decision trees are created using the traditional technique, or the recognition rate of the individual decision trees generated may be poor, both of which affect the final result. This study suggests a probability selection-based approach to identify each learned unique decision tree that satisfies both the variety and good and distinct requirements. For predicting the C_0 with covariate x_0 [18]. The specific formula is represented in Equation (2):

$$\frac{1}{M}\sum_{m=1}^{M} \hat{f}_m^*(x_0) \quad (2)$$

Where, $\hat{f}_m^*(x_0)$ denote the prediction of C_0 by m-th tree.

A. Evaluation Metrics

The performance of the model was assessed using a number of indicators, such as ROC analysis, f1-score, recall, accuracy, and precision. These metrics are detailed below:

Accuracy: Scales the frequency of the model being right among all the predictions of the model. Equation (3) states the mathematical representation:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Precision: Shows the number of the instances predicted positive that are True positives. Equation. (4) demonstrates the mathematical formulation:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall: Evaluates how many True Positive situations the model is able to identify. Equation (5) shows the formula:

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1-Score: The accuracy and recall harmonic mean, which integrates both metrics into one. The formula is depicted in Equation (6):

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

ROC Analysis: A curve, which shows the capability of a model to differentiate the classes by showing how the thresholds affect the genuine positive rate compared to the false positive rate.

IV. Results Analysis and Discussions

The experimental setup utilized a system powered by an Intel® Pentium® CPU G2030 running at 3.00 GHz, with a 64-bit Windows (X86 Ultimate) operating system, 1 TB of hard disk storage, and 4 GB of RAM. Table II presents the performance of a Random Forest (RF) model used for Mobile network traffic forecasting. The model has good predictive power with an accuracy of 98.79 which shows very reliable general predictions. Also, the RF model has achieved balanced classification performance, and the precision, recall, and F1-score are all at 95.0 and indicate that the model is suitable in the accurate recognition of the traffic patterns and minimizes the number of false positive and false negative results.

TABLE II. RESULTS OF RF MODEL FOR TRAFFIC FORECASTING IN MOBILE NETWORKS.

Metrics	**RF**
Accuracy	98.79
Precision	95.0
Recall	95.0
F1-Score	95.0

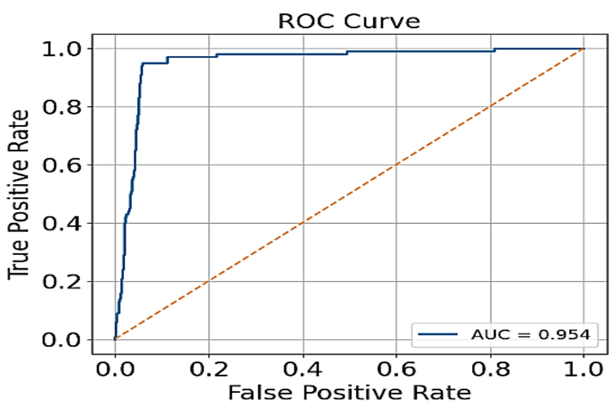

Fig 4: ROC Curve Analysis of the Model.

Figure 4 illustrates the ROC curve of the model indicating high degree of differentiating the classes since the curve is rapidly increasing towards the highest point on the left-hand side. The model maintains a high TPR and low FP at different thresholds, as seen by the huge AUC value, which shows that the model achieves a good overall classification performance.

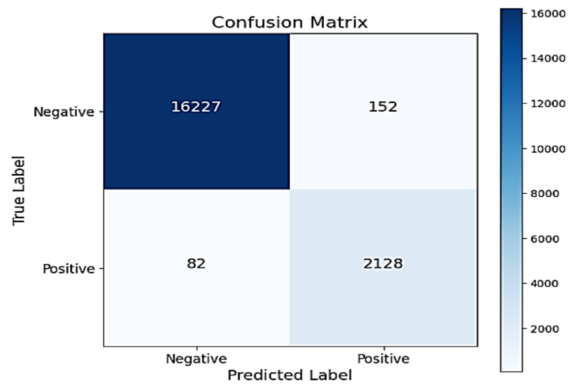

Fig 5: Confusion Metrics.

The confusion matrix is presented in Figure 5, and it is clear that the model accurately classifies the overwhelming majority of negative and positive cases, and a small number of misclassifications are observed. The high overall predictive accuracy and successful separation of the two classes is indicated by the high diagonal dominance.

A. Comparative Analysis

The proposed RF model and one of the traditional methods are thoroughly compared in this section, that is, MLP To provide fairness and consistency, all models were trained and tested within the same experimental conditions. As Table III indicates, the RF model is more effective in critical evaluation metrics than the other techniques and this indicates its high accuracy and high power in traffic forecasting in mobile networks.

TABLE III: COMPARISON FOR TRAFFIC FORECASTING IN MOBILE NETWORKS

Models	Accuracy
MLP [19]	95.0
RF	98.79

B. Discussion

It shows that mobile network traffic forecasting with the help of the Random Forest model has good and robust performance, and the comparison model has obvious disadvantages in question compared to the former when both models run in the same experimental conditions. The fact that it is always more predictive and exhibits a balanced classification nature underscores its strength when it comes to the ability to capture traffic patterns and limit errors. In general, the results suggest that the Random Forest is a more appropriate and efficient strategy to use in such processes of mobile network traffic forecasting.

V. Conclusion and Future Work

The prediction of traffic over mobile networks is indispensable to the effective management of resources and the optimization of networks, as well as the detection of anomalies in advance. The study comes to the conclusion that utilizing actual mobile activity data, the Random Forest model is a very accurate and dependable method for predicting mobile network traffic. Having shown high results in numerous assessment measures, such as an accuracy of 98.79, the model can be considered to be able to detect more intricate traffic tendencies and identify the various degrees of network activity with a low error rate. The results demonstrate the model's strength, which is better than the standard MLP technique and makes it a valid tool that can be effectively used in mobile network settings. This robust forecasting can help network operators to make sound decisions as far as capacity planning, congestion management, and optimization of the overall services are concerned. Moreover, the paper presents the importance of combining machine learning with real-time network information to support new requirements of communication systems. The results serve as the foundation for additional study aimed at improving prediction quality, increase the size of data, and consider more sophisticated learning models to predict dynamic traffic.

The future studies can consider more sophisticated ML and DL models to expand the accuracy and adaptability of forecasts. Increasing the amount of the data with longer time intervals and regions helps enhance generalization. Real-time data streams and features that are particular to networks can also be incorporated to enhance the practical deployment in a volatile mobile network environment.

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