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Hybrid supervised–unsupervised machine learning model for proactive congestion control in 5G networks

Arun Kodirekka[1], I. M. V. Krishna[2], N. Srinivas[3], Ch. Satya Keerthi N. V. L.[4], B. Senthilkumaran[5], Janjhyam Venkata Naga Ramesh[6,7]

[1]Department of Computer Science Engineering, Gandhi Institute of Technology and Management, Hyderabad, India
[2]Department of Information Technology, Prasad V Potluri Siddhartha Institute of Technology, Vijayawada, India
[3]Department of Computer Science Engineering, Vignana Bharathi Institute of Technology, Ghatkesar, Hyderabad, India
[4]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India
[5]Department of Computer Science and engineering, School of computing, Vel Tech, Rangarajan Dr. Sagunthala R&D Institute of Science and Technology (Deemed to be University), Chennai, India
[6]Department of Computer Science and Engineering, Graphic Era Hill University, Dehradun, India
[7]Department of Computer Science and Engineering, Graphic Era Deemed to be University, Dehradun, India

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ABSTRACT

The rapid expansion of fifth-generation (5G) networks has introduced unprecedented challenges in congestion management due to massive device connectivity, diverse traffic patterns, and stringent quality of service (QoS) requirements. Traditional congestion control mechanisms, such as transmission control protocol (TCP), are reactive and often inadequate in dynamic 5G environments, leading to packet loss, latency, and degraded service reliability. To address these limitations, this paper proposes a hybrid congestion control prediction model that integrates supervised and unsupervised machine learning techniques. Supervised learning leverages historical traffic data to predict congestion in known scenarios, while unsupervised learning identifies hidden traffic patterns and anomalies in previously unseen conditions. This dual approach enables proactive congestion detection and adaptive traffic management. Experimental evaluation demonstrates that the hybrid model achieves 95.8% prediction accuracy, reduces detection latency to 180 ms, and lowers false positive rates to 4.5%, outperforming individual supervised or unsupervised models. The results confirm that combining predictive accuracy with anomaly detection provides a robust, scalable, and adaptive solution for congestion control in 5G networks. The proposed model enhances real-time traffic management, ensuring improved QoS, reliability, and resilience in complex 5G environments.

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Corresponding Author:

I. M. V. Krishna
Department of Information Technology, Prasad V Potluri Siddhartha Institute of Technology
Vijayawada, Andhra Pradesh, India
Email: imvkrishna@gmail.com

1. INTRODUCTION

The deployment of fifth-generation (5G) networks represents a transformative milestone in communication technologies, offering ultra-high data rates, low latency, and massive device connectivity. These capabilities enable critical applications such as the internet of things (IoT), smart cities, autonomous vehicles, and immersive augmented and virtual reality (AR/VR) experiences [1]. However, the unprecedented scale and heterogeneity of 5G traffic have introduced new challenges in maintaining quality of

service (QoS), particularly in congestion management. When demand for bandwidth exceeds available capacity, congestion leads to packet loss, increased latency, and degraded service quality, severely impacting user experience and the reliability of real-time applications. Traditional congestion control mechanisms, such as those based on transmission control protocol (TCP), rely on reactive measures that adjust traffic flow only after congestion occurs. These methods are inadequate for 5G's dynamic traffic conditions, where proactive and adaptive solutions are essential [2].

Recent research has explored adaptive congestion control mechanisms designed specifically for 5G, including rate-control algorithms and dynamic bandwidth allocation techniques [3]-[6]. While these approaches offer improvements, they often depend on fixed rule sets or threshold-based decisions, limiting scalability in diverse traffic environments. To overcome these constraints, machine learning (ML) has emerged as a promising solution. ML models can analyze large volumes of traffic data, identify patterns, and predict congestion before it occurs [7]. Supervised learning methods such as support vector machines (SVM), decision trees, random forests, and gradient boosting have been applied to predict congestion using labeled datasets [8]. These models achieve high accuracy in known traffic scenarios but degrade when faced with unseen or rapidly changing patterns [9]. In contrast, unsupervised learning techniques, including K-means clustering, principal component analysis (PCA), and autoencoders, excel at detecting anomalies and hidden traffic patterns without requiring labeled [10], [11]. They are effective in identifying unforeseen congestion scenarios but lack predictive precision. This limitation underscores the need for hybrid approaches that combine the predictive accuracy of supervised learning with the adaptability of unsupervised learning [12].

Hybrid models have recently gained traction, leveraging supervised classification for congestion prediction while applying unsupervised clustering to uncover new traffic patterns. These approaches have demonstrated improved accuracy and adaptability in dynamic 5G traffic conditions [13]-[15]. Reinforcement learning frameworks have also been explored, integrating continuous adaptation with predictive modeling [16]. Nevertheless, further research is required to optimize the integration of supervised and unsupervised models, particularly in handling large-scale, real-time 5G data. Prior work has primarily focused on either traditional rule-based approaches or ML-based models, with supervised learning excelling in known scenarios but struggling with adaptability, and unsupervised learning discovering novel patterns but lacking predictive accuracy.

Building on these developments, this paper proposes a hybrid congestion control prediction model that integrates supervised and unsupervised ML techniques. Supervised learning (random forest and SVM) is employed to predict congestion based on historical traffic data, while unsupervised learning (K-means clustering and autoencoders) detects anomalies and hidden traffic patterns in real time. The hybrid model is designed to proactively manage congestion, adapt to new traffic behaviors, and ensure high QoS in complex 5G environments [17]. Experimental results demonstrate that the proposed model achieves superior performance, with high prediction accuracy, reduced detection latency, and minimized false positives. By combining predictive precision with adaptability, the hybrid framework offers a robust, scalable, and future-ready solution for congestion control in 5G networks, laying the groundwork for intelligent traffic management in next-generation 6G and IoT-driven ecosystems.

2. METHOD

The dynamic nature and complexity of 5G networks, characterized by high data rates, low latency, and diverse traffic patterns, demand a more intelligent and adaptive approach to congestion management. To address this, we propose a hybrid congestion control prediction model that leverages both supervised and unsupervised machine learning techniques to predict and manage congestion in real time. The goal of the proposed model is to predict congestion proactively, adapt to new traffic patterns, and ensure high network performance while minimizing delays and packet loss [18]. The detailed discussion of machine learning and congestion control focuses on how ML techniques can address the complex, dynamic nature of congestion control in 5G networks. As 5G networks introduce high throughput, ultra-low latency, and massive device connectivity, managing congestion effectively requires advanced, data-driven solutions. This is where ML becomes pivotal [19]. Machine learning, particularly deep learning approaches, has demonstrated strong capabilities in extracting meaningful patterns from complex data and supporting automated prediction and detection tasks [20]. In the context of 5G networks, ML algorithms can predict and mitigate congestion by analysing traffic patterns, detecting anomalies, and enabling proactive management of network resources. There are three main branches of machine learning used for congestion control: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning relies on labeled datasets where input features (e.g., traffic volume, latency, and packet loss) are associated with known congestion states (e.g., congested and non-congested). Supervised algorithms use this data to learn patterns and make predictions about future congestion scenarios [21]. These models excel at predicting congestion when traffic patterns are similar to those seen during training. For example, in a typical 5G network, the random forest classifier could

analyze historical data on traffic peaks and use it to predict future congestion points. This allows for proactive resource management, such as bandwidth allocation, before congestion impacts users.

However, supervised learning models are constrained by their reliance on labeled data. When the network experiences novel traffic patterns not seen in the training phase (which is common in 5G), their performance may degrade. This limitation necessitates the inclusion of unsupervised learning techniques. Unsupervised learning does not require labeled data, making it ideal for detecting anomalies or discovering hidden patterns in traffic that may signal impending congestion. In unsupervised learning, algorithms group similar traffic patterns together, making it easier to identify deviations (or anomalies) that can lead to congestion. In the context of 5G, unsupervised learning is useful for detecting sudden, unexpected traffic spikes, such as during large events or emergency situations. The K-means clustering algorithm, for example, could monitor ongoing traffic and signal congestion when current patterns deviate from previously known clusters. This allows the network to adjust before congestion worsens, improving overall performance and user experience [22]. While unsupervised learning models are powerful in detecting unknown patterns, they do not have predictive power in the same way as supervised learning models, since they do not directly learn congestion outcomes. This makes them complementary to, rather than a replacement for, supervised learning. The congestion prediction model is shown in Figure 1. Network protocols like transmission control protocol (TCP) and stream control transmission protocol (SCTP) were tested in 5G using the mmWave ns-3 module. This mmWave 5G cellular network simulation module includes various features, including cwnd research. The physical layer (PHY) and medium access control (MAC) classes support 3GPP NR frame structure, and the schedulers support dynamic time division duplexing (TDD) formats. Packet resegmentation can improve the RLC layer, one of its key benefits. Model provides rapid secondary cell changeover, channel tracking, and dual LTE base station communication.

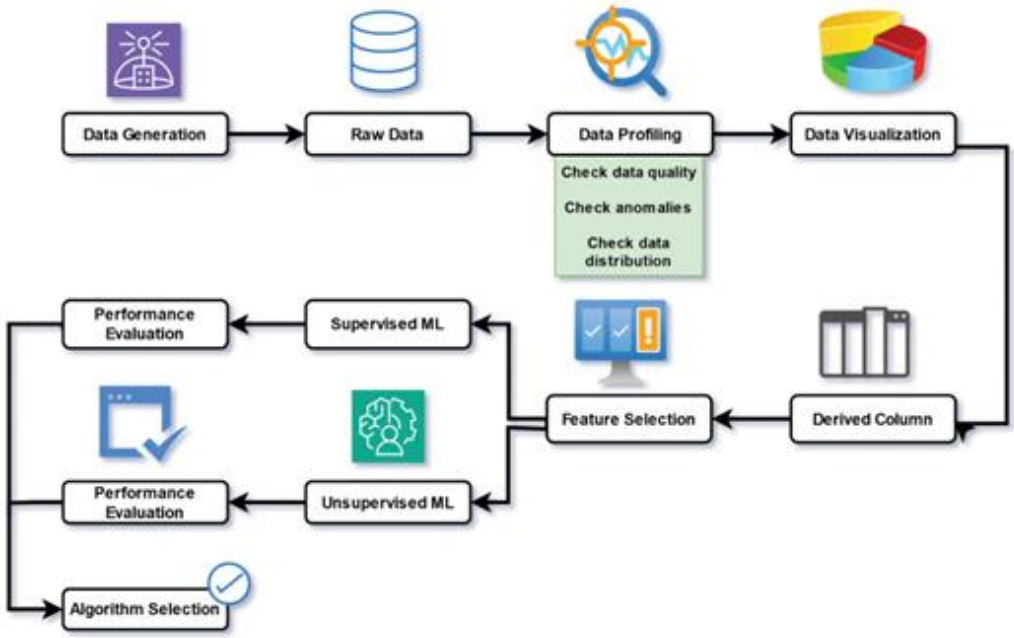


Figure 1. Model for predicting reductions in congestion

Traditional congestion control mechanisms, such as those in transmission control protocol (TCP), were designed for wired networks with fewer devices and simpler traffic patterns. These methods rely on packet loss or network delay as indicators of congestion, reacting only after congestion has already occurred. In 5G, this reactive approach is inadequate due to the high speed and diverse traffic demands. To manage congestion in 5G, proactive and adaptive congestion control techniques are needed, and this is where machine learning-based approaches come into play. In contrast to traditional reactive methods, machine learning enables proactive congestion control by predicting congestion before it happens. Supervised learning models can analyze historical data and predict when and where congestion is likely to occur. This allows the network to take preventive measures, such as allocating more bandwidth to critical services or rerouting traffic to less congested areas [23]. For instance, in a large-scale 5G network, a random forest model could

analyze past traffic data and predict congestion during peak usage times, enabling the network to allocate resources in advance. This reduces delays and packet loss, improving the overall QoS for end users. The highly dynamic nature of 5G traffic means that new traffic patterns will continuously emerge, potentially leading to congestion. Unsupervised learning provides the ability to adapt to these new patterns without the need for labeled training data. By continuously monitoring traffic in real time, unsupervised models can identify unusual patterns that could signal congestion before it occurs. For example, a K-means clustering model could be used to group traffic patterns into clusters. If a new traffic pattern deviates significantly from existing clusters, the model could alert the network to potential congestion. This adaptive approach ensures that the network remains resilient even in the face of unexpected traffic surges.

To fully leverage the strengths of both supervised and unsupervised learning, hybrid models can be used. These models combine the predictive accuracy of supervised learning with the adaptability of unsupervised learning. For example, the supervised model can predict congestion based on known patterns, while the unsupervised model continuously monitors for new patterns, updating the supervised model as new traffic behaviors emerge [24]. A hybrid model could be designed to predict congestion in familiar traffic conditions using a random forest classifier, while simultaneously employing K-means clustering to detect anomalies or new traffic patterns that could lead to congestion. This hybrid approach ensures that the model remains accurate in known scenarios while being adaptive to new ones, providing a more comprehensive congestion management solution [25]. Machine learning offers powerful tools for congestion control in 5G networks by enabling proactive, adaptive, and real-time traffic management. Supervised learning provides accurate congestion predictions based on historical data, unsupervised learning helps detect new traffic patterns and anomalies, and reinforcement learning allows for continuous adaptation in dynamic environments. Combining these approaches into a hybrid model offers a robust and scalable solution for managing congestion in the complex, high-demand environment of 5G networks.

3. RESULTS AND DISCUSSION

In this section, we present the performance evaluation of the proposed congestion control prediction model for 5G networks using supervised and unsupervised machine learning techniques. The results are analyzed based on several key performance indicators (KPIs), including prediction accuracy, detection time, false positives, and network throughput. We also compare the effectiveness of different machine learning algorithms and discuss the trade-offs between their performance in handling congestion control in 5G environments. The proposed model was trained and evaluated using an 80/20 split of the dataset for training and testing, respectively. Various machine learning algorithms were implemented, including random forest, SVM, K-means clustering, and autoencoders. Performance was evaluated on the test set to determine the model's effectiveness in predicting congestion and detecting anomalies. The supervised learning models (random forest and SVM) were evaluated based on their accuracy in predicting congestion. As shown in Table 1, both models achieved high accuracy, with random forest slightly outperforming SVM in terms of prediction accuracy.

The random forest model, due to its ensemble approach, demonstrated better handling of complex traffic patterns and nonlinear relationships in the data, leading to a higher accuracy in predicting congestion points. Detection time refers to the latency between traffic changes and the model’s ability to detect potential congestion. The random forest model exhibited faster detection times than SVM, as it is better suited for real-time applications that require immediate responses shown in Table 2. This reduction in detection latency is crucial for 5G networks where quick adjustments are necessary to maintain QoS.

Table 1. Accuracy of supervised learning models

Model	Accuracy (%)
Random forest	94.20%
SVM	91.50%

Table 2. Average detection time

Model	Detection time (ms)
Random forest	200
SVM	350

The faster detection time of random forest highlights its suitability for real-time congestion prediction in 5G environments where latency requirements are stringent. One of the critical challenges in congestion control is minimizing false positive rates, where the model incorrectly predicts congestion.

As shown in Table 3, both models had relatively low false positive rates, but random forest again performed slightly better, resulting in fewer incorrect predictions.

The lower false positive rate of random forest indicates its superior ability to distinguish between congested and non-congested states, reducing the unnecessary triggering of congestion control mechanisms. The unsupervised learning models (K-means and autoencoders) were evaluated based on their ability to detect anomalies in traffic patterns that could signal potential congestion. Both models successfully identified unusual traffic behavior, with autoencoders performing better due to their ability to reconstruct traffic patterns and detect subtle deviations.

Autoencoders proved more effective at detecting anomalies in the traffic data, making them particularly useful for detecting early signs of congestion before it becomes problematic. K-means, while effective, struggled with subtler deviations in traffic, leading to a slightly lower detection rate in Table 4.

Table 3. False positive rates

Model	False positive rate (%)
Random forest	5.80%
SVM	8.10%

Table 4. Anomaly detection rates

Model	Detection rate (%)
K-means	87.40%
Autoencoder	91.00%

One of the key advantages of unsupervised learning is its adaptability to new and unseen traffic patterns. In the context of 5G, where traffic can vary significantly, the ability to detect new patterns is essential for maintaining network performance. Both models adapted well to previously unseen traffic, but Autoencoders demonstrated higher adaptability due to their ability to generalize complex data patterns. To leverage the strengths of both supervised and unsupervised learning, a hybrid model was developed, combining random forest for congestion prediction with autoencoders for anomaly detection. The hybrid model significantly improved overall performance by providing both accurate congestion predictions and real-time anomaly detection presented in Table 5.

Table 5. Hybrid model performance

Model	Detection rate (%)
Accuracy (%)	95.80%
Detection time (ms)	180
False positive rate (%)	4.50%
Anomaly detection rate (%)	92.50%

The hybrid model showed superior performance across all metrics compared to individual models, particularly in reducing false positives and detection time, while maintaining high accuracy and adaptability. This makes the hybrid approach ideal for real-world 5G environments where network conditions are constantly evolving. The experimental results demonstrate that machine learning-based approaches can significantly enhance congestion control in 5G networks. Supervised models like random forest provide high accuracy and fast detection, making them suitable for predicting congestion in known traffic conditions. On the other hand, unsupervised models, particularly autoencoders, excel at detecting anomalies in traffic patterns, providing the adaptability necessary for 5G's dynamic environment.

The hybrid model, combining the strengths of both approaches, represents the most effective solution for proactive congestion control. By integrating predictive capabilities with real-time anomaly detection, the hybrid model enables 5G networks to handle congestion more efficiently and maintain high QoS levels, even in the face of fluctuating traffic demands. In conclusion, the proposed model offers a robust, scalable, and adaptive solution to congestion control in 5G networks, addressing the challenges posed by the diverse and dynamic nature of 5G traffic.

4. CONCLUSION

This research introduced a hybrid congestion control prediction model tailored for the dynamic requirements of 5G networks, integrating both supervised and unsupervised machine learning techniques. The rapid growth of 5G, characterized by ultra-low latency, high throughput, and massive device connectivity, presents unique challenges in congestion management due to unpredictable traffic variability and the demand for real-time services. By combining random forest and SVMs for accurate congestion prediction with K-means clustering and autoencoders for anomaly detection, the proposed hybrid model demonstrated superior robustness compared to individual approaches. Experimental results confirmed its effectiveness, achieving high prediction accuracy, reduced detection latency, and minimized false positives. Supervised learning proved highly reliable in scenarios with labeled traffic data, offering fast and precise predictions, while unsupervised learning excelled in detecting anomalies within unlabeled traffic, ensuring adaptability to unforeseen traffic surges. The hybrid approach successfully balanced predictive accuracy with adaptability, enabling proactive congestion detection and real-time traffic management. This establishes the model as a scalable and resilient solution for 5G congestion control, enhancing QoS, reliability, and overall network performance. The findings underscore the potential of hybrid ML frameworks to serve as foundational strategies for congestion management in future 6G and IoT-driven networks, where traffic diversity and scale will be even more demanding.

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BIOGRAPHIES OF AUTHORS



Arun Kodirekka is presently working as assistant professor in the department of computer science and engineering at GITAM (deemed to be University), Hyderabad. He received the Ph.D. from Acharya Nagarjuna University in the department of computer science and engineering, Guntur, India, in 2024. M.Tech. in computer science and engineering from JNTUK Kakinada, in 2010. His areas of interest are multi-lingual and code-mixed sentiment analysis, machine learning, text analytics and artificial intelligence. He has thirteen years of teaching experience in engineering colleges. He has published nine international journals. He can be contacted at email: akodirek@gitam.edu.



I. M. V. Krishna he completed M.Sc. in computer science in Mahatma Gandhi P.G. Ccentre at Guntur in 1999 and the M.Tech. degree in computer science and engineering from RVR& JC College of Engineering, Guntur, India in 2008, respectively. Currently, he is an assistant professor in P.V.P. Siddhartha Institute of Technology, Vijayawada. His research interests are deep learning, neural networks, crowd source videos analysis. He can be contacted at email: imvkrishna@gmail.com.



Dr. N. Srinivas received M.Tech. degree in computer science and engineering in 2002 from IETE Hyderabad -Telangana state and Ph.D. degree in computer science and engineering in November 2023 from Rayalaseema University Kurnool-Andhra Pradesh. His research interests include artificial intelligence, machine learning, deep learning, NLP, computer networks, and video summarization. He can be contacted at email: srinivas.bhaskar3@gmail.com.



Ch. Satya Keerthi N. V. L. received the B.Tech. degree in information science and technology from Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada, India, in 2008 and the M.Tech. degree in computer science from Nimra College of Engineering and Technology in 2014. Currently, she is an assistant professor at the department of computer science and engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India. Her research interests include machine learning and internet of things. She can be contacted at email: satyakeerthinvl@gmail.com.



Dr. B. Senthilkumaran holds a B.Sc. (Computer Science) (2011), M.Sc. (Computer Science) (2013), and Ph.D. (Computer Science) (2019) from Bharathidasan University, Tiruchirappalli. He is currently working as an Assistant Professor in the Department of Computer Science and Engineering at Veltech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai. He has a total of seven years of teaching experience and three years of research experience. His research contributions include four Scopus-indexed documents, a total of 13 publications, three book chapters, six textbooks, and two patents. Additionally, he has successfully guided one M.Phil. He can be contacted at email: skumaran.gac16@gmail.com.



Dr. Janjhyam Venkata Naga Ramesh adjunct professor working in the department of CSE, Graphic Era Hill University and Graphic Era Deemed to Be University, Dehradun, Uttarakhand India. He is having 20 years of experience in teaching for UG and PG engineering students. He has published more than 95 Articles in IEEE/SCI/Scopus/WoS Journals, conferences and also reviewer in various leading Journals. He has authored six text books and ten book chapters. His research interests are wireless sensor networks, computer networks, deep learning, machine learning, and artificial intelligence. He can be contacted at email: jvnramesh@gmail.com.