

A Comparative Study between Logistic Regression and SVM for Resource Management in Network Slicing

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Abstract: Network slicing is an essential component of 5G and subsequent networks. It enables administrators to partition shared physical infrastructure into several virtual segments, each with distinct Quality of Service (QoS) requirements. Effective and adaptable real-time resource management is essential for optimal performance in dynamic situations, characterized by low latency and high throughput. Despite the increasing body of literature on machine learning in communication networks, there is a paucity of direct comparisons between Logistic Regression (LR) and Support Vector Machines (SVM) concerning network slicing resource management. Prior comparisons have predominantly concentrated on sectors such as education, healthcare, and the Internet of Things (IoT), resulting in minimal exploration of slicing prospects. This study rectifies this gap by doing a comparative analysis of Logistic Regression and Support Vector Machine models utilizing the CICIDS2017 dataset in a network slicing simulation environment. Both models were utilized independently, employing class balancing and feature selection to forecast overload. We evaluated their performance for accuracy, ROC AUC, latency, jitter, and throughput across network slices. Results indicate that SVM exhibited somewhat superior classification accuracy; however, LR consistently surpassed SVM in critical network-level parameters, including reduced delay, enhanced throughput, and improved jitter stability. These results indicate that LR is an effective option for the real-time management of network slicing resources due to its practicality and comprehensibility. In conclusion, LR is a dependable primary option for scholars and professionals pursuing effective, low-latency solutions, improving the superior classification accuracy of SVM with enhanced overall network performance.

Keywords: Logistic Regression; Network Slicing; Resource Management; Support Vector Machine; Virtual Networks.

INTRODUCTION

Network slicing is an umbrella word encompassing virtualization methods that design, partition, and organize a physical infrastructure's computing and communication resources to accommodate a variety of use cases in a flexible manner. In order to meet the diverse requirements of new 5G verticals and applications, this resource partitioning may be tailored in a cost-effective manner (Ali, 2022). To facilitate resource sharing, Network Slicing turns traditional structures into adaptable components that run on the chosen architecture, allowing for the formation of multiple logical networks on top of a shared physical infrastructure. This is seen as the essential part of 5G and future networks (Munther et al., 2021). Streaming services and social media services are anticipated to share a portion of 5G's physical infrastructure. Our definition of a logical network slice centers on the integration of virtual resources and network functions, regardless of how isolated the tenants' resources may be (Wijethilaka & Liyanage, 2021).

Selecting a proper resource management in real time is a key component of the complicated process of reshaping mobile networks for slicing. A large number of tenant-run logical network instances residing in the same physical infrastructure and dynamically sharing physical resources is truly necessary for sliced networks (Al-Dabbagh, 2024). This adds a lot of complexity and renders human-driven techniques of network administration useless when compared to prior, non-sliced systems where the network operator handled everything (Li et al.,

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2018). In real-time communication in particular, operators should strive for automatic slice management throughout data interchange. The poor guides in how to select a proper AI algorithm for network slice resource management.

This research aims to compare the most common AI techniques namely LR and SVM in the field of network slicing. These techniques utilized to manage and forecast the network traffic based on specific parameters and factors. The comparison have been conducted from simulation along with slicing datasets. Results help to make a wise decision in which AI technique is better and for which circumstancing and Guidelines for choosing between LR and SVM based on network conditions.

Logistic Regression and Support Vector Machine have been thoroughly compared in numerous fields, although there is a conspicuous lack of research that specifically assesses their efficacy in the niche area of network slicing resource management. Previous research predominantly emphasizes extensive applications, including education, medical diagnosis, and general traffic classification, while neglecting the specific needs of dynamic slicing contexts (Patel et al., 2025), (Malkoc & Kholidy, 2023). This paper addresses this deficiency by offering a comprehensive comparative analysis of LR and SVM models specifically utilized in network slicing contexts. The originality of this study resides in its focus on domain-specific performance, demonstrating that while SVM attains somewhat higher classification accuracy, LR yields superior results in delay, throughput, and jitter. These results show the trade-off between how complicated a model is and how well a network works, giving useful information to both researchers and practitioners.

LITERATURE REVIEW

Authers in (Kumar & Ahmad, 2022) have done a comparative study between logistic regression algorithm and the supporting vector machine (SVM) in forecasting how well students would do in online programming courses. The results showed that logistic regression is the best basic and effective linear model for binary classification since it is easy to understand and use in schools that may not have access to higher technical resources. The study showed that this algorithm works well for forecasting how well children will do in school, especially when they are learning online. The supporting vector machine, on the other hand, was able to determine the optimum super plane that separates classes and worked well with nonlinear data when the right kernel functions were used. But since they were so complicated, it was harder to explain them than it was to explain logistical decline. The logistic regression had the highest AUC-ROC value on the test set at 93.54%, while the SVM algorithm had an AUC-ROC value of 85.58%. This means that the logistic regression was better at generalizing and being useful for predicting student performance in online programming courses early on. This shows that simple models may be better for real-world educational use.

In (Malkoc & Kholidy, 2023), Authers comparison study have been done between different machine learning in 5G network infrastructure. The researchers utilized the Logistic Regression technique and the Support Vector Classifier (SVM) to look at the features of network chips and sort traffic into groups for virtual reality, gaming, self-driving cars, and industrial automation. The findings were great: the Logistic Regression technique got 100% accuracy, which was the best of all the models evaluated, and the SVM classifier did an excellent job of classifying network chips. The study employed a dataset with 31,584 rows that included LTE/5G indications, time, packet loss, packet delay, IoT characteristics, and GBR/Non-GBR standards. The ambiguity matrix study indicated that all three segments had flawless recall rates (100%) when using Logistic Regression. This proves that these algorithms function well for controlling 5G network architecture.

In (Sutanto et al., 2024), Authers have looked closely at the logistic regression technique and the supporting vector machine (SVM) as well as other algorithms for sorting water quality based on pollutant coefficients. The study discovered that logistic regression is a simple and practical linear model that is often used to address classification problems where the input and output variables are linearly related. This is because it is simple to understand and use. But it doesn't function as well when the variables aren't related in a straight line or when the data is spread out in a convoluted way. On the other hand, the supporting vector machine is great at working with nonlinear data because it finds the optimum super plane that separates classes in the data space. It also handles outliers well. One problem with SVM is that it is sensitive to transaction tuning, which implies that it needs more intricate transaction settings to perform well. The logistic regression got 90.19% of the answers right, while the supporting vector machine got 93.25% of the answers right. This proves that SVM is better at classifying water quality, especially when the data is convoluted and not in a straight line.

In (Lynam et al., 2020), the authors have done valuable assessment of the logistic regression method, the supporting vector machine (SVM), and other machine learning algorithms to see how well they could tell the difference between type I and type II diabetes in young adults. The study found that logistic regression is a well-known statistical algorithm for binary results that uses maximum probability estimation. It is fully parametric and does not need to be adjusted for super coefficients because the coefficients are changed to allow properties to depend on each other. This makes them useful for inference, estimation, interpretation, and prediction. On the other hand, the supporting vector machine is a quadratic optimization problem that tries to minimize penalties and

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maximize margin width. It does this by building nonlinear decision boundaries (super levels) that separate the two classes and using a kernel trick to make the margin between them as wide as possible. The estimates that come out of this process are a re-scaled version of the original classifiers' scores through a logistic transformation. However, because SVM is sensitive to transaction tuning, the model needs more complicated transaction settings to work at its best. Logistic regression had the highest AUC-ROC value in external validation at 95%, while the supporting vector machine had 94%. This shows that logistic regression is better at generalizing and being useful in clinical settings, especially when using a small number of strong and well-understood predictive variables.

The work in (Maros et al., 2021) have done a comparison of the logistic regression method, the supporting vector machine (SVM), and other machine learning algorithms to make computer-aided reporting tools for medical imaging in a study. The study found that logistic regression is a classic statistical algorithm for binary results that uses maximum probability estimation and is fully parametric. This means that there are no model super coefficients to adjust and the coefficients can be changed to allow properties to depend on each other. This makes them useful for inference, estimation, interpretation, and prediction. On the other hand, the supporting vector machine is a quadratic optimization problem that involves lowering penalties and raising margin width. The two groups are separated by creating nonlinear decision limits (super planes) using the kernel trick, which maximizes the space between them. The scores of the original works are then rescaled through a logistic transformation to get the final estimates. The linear supporting vector machine (SVM-LK) had the highest accuracy (87.4%) and the lowest results (BS: 0.22 and LL: 0.37) with a similar AUC of about 80% compared to other algorithms when applied to properties extracted by human experts. SVM had 82.5% accuracy on findings and 85.4% accuracy on impressions, which shows that SVM is better at handling complex and nonlinear data in medical settings.

**ALGORITHM OVERVIEW
LOGISTIC REGRESSION**

Logistic regression is one of the basic supervised learning algorithms that is widely used in classification tasks. Unlike a linear slope that predicts continuous values, a logistic slope aims to predict the possibility of a particular event (usually binary, such as yes/no, 0/1) based on a set of independent variables. The model relies on the X-Function to convert linear outputs into probabilities between 0 and 1, making it particularly suitable for problems that require the data to be classified into separate categories (Nobel et al., 2024).

APPLICATIONS IN NETWORK RESOURCE MANAGEMENT

In the context of network resource management, especially given the complexity of 5G networks and beyond, logistical regression has become a useful tool among the range of AI and machine learning methods applied to increase reliability and efficiency. To deal with issues related to service diversity, low latency needs, and high density of connected devices, 5G networks need dynamic and adaptive resource management. Here, logistic regression finds application in various important areas of resource management (Fernandes et al., 2025). Table (1) indicates the most important modern applications of logistic regression in network resource management.

SUPPORT VECTOR MACHINE (SVM)

Complex network resource management is one of the many casing and regression applications in which resilient and well-known SVM technology has shown success. The primary goal of SVM is to produce the ideal "super-level" with the widest possible margin separating many data classes in the feature space, thereby improving the generalizability of the model to new data (E.V.N. Jyothi1 et al.,2025).

Applications of Support Vector Machine (SVM) in Network Resource Management

In the context of network resource management, SVM has found important applications, especially in light of the increasing complexity of networks and the need for intelligent and efficient resource management. most prominent modern uses in table (2).

Ref.	Application Area	Description & Implementation	Key Benefits & Capabilities
(Han & Schotten, 2020)	Real-time Overload Detection	Logistic regression is able to determine if a network is normal or overcrowded by looking at performance indicators like throughput, latency, and packet loss rates.	<ul style="list-style-type: none"> • Fast binary classification • Flexible threshold adjustment • Proactive resource scaling • Real-time decision making • Prevents system overload

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(Abood et al., 2023)	Resource Allocation Decisions	Logistic regression algorithms can predict resource contention based on current network conditions and prior patterns. This lets smart decisions about how to allocate resources avoid bottlenecks and make the best use of network resources across slices.	<ul style="list-style-type: none"> • Contention prediction • Bottleneck prevention • Optimal resource distribution • Historical pattern analysis • Multi-slice optimization
(Kumar & Ahmad, 2022)	Quality of Service (QoS) Prediction	Logistic regression uses real-time network metrics to forecast service class QoS breaches. The predictive capability lets you make changes ahead of time to keep service level agreements and make the user experience better across different network slices.	<ul style="list-style-type: none"> • QoS violation prediction • SLA maintenance • Enhanced user experience • Service class differentiation • Proactive adjustments
(Salau & Beyene, 2024)	Traffic Classification	Based on features derived from streams (for example, packet size, time intervals, and protocols), SVM is applied to define several types of network traffic flows (for example, DNS, Ping, Voice, and Telnet). Understanding network activity and using appropriate resource management techniques depends on this type of classification.	<ul style="list-style-type: none"> • Multi-class traffic classification • Protocol-based categorization • SDN integration capability • Centralized control support • Effective data collection
(Serag et al., 2025)	Improve Quality of Service (QoS)	Based on the traffic classification provided by SVM, network administrators can implement mechanisms to improve QoS. This includes prioritizing delay-sensitive traffic or ensuring adequate bandwidth allocation for critical applications, improving overall network performance and user experience.	<ul style="list-style-type: none"> • Delay-sensitive traffic prioritization • Bandwidth allocation optimization • Critical application support • Network performance improvement • Enhanced user experience
(E.V.N. Jyothi et al., 2025)	Resource Allocation and Congestion Forecasting	Based on certain performance parameters, SVM – especially with appropriate cores such as an RBF (or Gaussian) kernel – can be applied to classify network states – such as congestion prediction. Gaussian SVM can effectively classify 5G network congestion, thereby guiding proactive resource allocation decisions.	<ul style="list-style-type: none"> • Network state classification • Congestion prediction • RBF kernel optimization • 5G network support • Proactive resource allocation

METHOD

DATASET AND FEATURES

Dataset Overview

This study utilizes the "Wednesday-workingHours.pcap_ISCX.csv" file from the CICIDS2017 dataset. It comprises statistics on network traffic gathered during standard working hours. The dataset comprises a comprehensive collection of network flow records that replicate authentic network environments. This renders it ideal for tasks such as network slicing and overload prediction (Sharafaldin et al., 2018).

Attributes of the Dataset:

- The total number of network flow records is 692,703.
- Total characteristics: 74 distinct categories of network traffic attributes

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- Missing Values: 1,008 items (0.15% of the total dataset)
 - Data Interval: Traffic patterns during business hours on Wednesday
 - The file format is CSV (Comma-Separated Values).
- The dataset shows a genuine class imbalance that is similar to what happens in real networks:
- Normal traffic: 506,323 samples (73.1%).
 - Overload Traffic: 186,380 samples, or 26.9%.

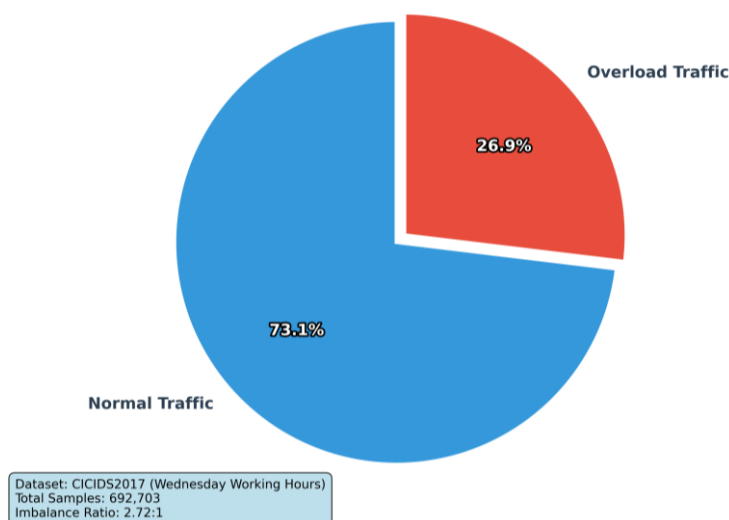


Figure (1) CICIDS2017 Dataset - Class Distribution

Data Generation and Traffic Modeling

The simulation utilizes artificial traffic patterns with authentic network traffic data sourced from the CICIDS2017 dataset (Wednesday-workingHours.pcap_ISCX.csv, 692,703 samples). The actual dataset comprises network flow parameters such as packet sizes, inter-arrival times, flow durations, and protocol distributions. Synthetic traffic generation techniques provide additional data under controlled overload conditions to equilibrate normal and congested network situations. Traffic generation adheres to Poisson distribution patterns, characterized by increasingly prolonged inter-arrival intervals, reflecting the behavior of a network under varying load conditions.

Original Dataset Features

Comprehensive Network Features Classification for Network Slicing Analysis (Table 3):

Table (3) Comprehensive Network Features Classification for Network Slicing Analysis

Feature Name	Description
Flow-based Features	
Flow Duration	Duration of network flows in microseconds
Total Fwd Packets	Total forward packets in the flow
Total Backward Packets	Total backward packets in the flow
Flow Bytes/s	Flow rate in bytes per second
Flow Packets/s	Flow rate in packets per second
Packet Size Features	
Total Length of Fwd Packets	Total bytes of forward packets
Total Length of Bwd Packets	Total bytes of backward packets
Fwd Packet Length Max/Min/Mean/Std	Statistical measures of forward packet lengths
Bwd Packet Length Max/Min/Mean/Std	Statistical measures of backward packet lengths
Timing Features	
Fwd IAT Total/Mean/Std/Max/Min	Forward direction timing statistics
Bwd IAT Total/Mean/Std/Max/Min	Backward direction timing statistics
Flow IAT Mean/Std/Max/Min	Overall flow timing statistics
Advanced Network Features	
Fwd PSH Flags	Forward push flags count
Bwd PSH Flags	Backward push flags count
Fwd URG Flags	Forward urgent flags count
Packet Length Mean/Std/Variance	Overall packet size statistics
Down/Up Ratio	Download to upload ratio

Engineered Simulation Features

To emulate network slicing, additional features were incorporated to demonstrate the network's real-time behavior via a comprehensive monitoring system that encompasses four critical performance domains. The resource utilization domain establishes fundamental metrics by quantifying current slice usage rates as normalized capacity percentages (0–1), monitoring temporal variations in resource consumption patterns, and employing second-derivative analysis to identify trends in usage acceleration indicative of impending capacity transitions. The evaluation of service quality examines the integrity of transmission and its performance attributes. It employs packet loss quantification to assess reliability, jitter measurements in milliseconds to evaluate delay variance and network stability, average packet transmission latency analysis, and packet efficiency calculations that juxtapose the number of successful receptions with the number of transmission attempts. Queue management settings furnish critical insights into system congestion by tracking real-time packet queue use and aggregating normalized packet counts across designated time intervals. This enables us to identify bottlenecks preemptively. The throughput characterization component evaluates data handling efficiency by measuring the transmission rate in bytes per second, doing statistical analysis of average message sizes, and tallying the number of messages successfully received over time. This establishes a multidimensional feature space that facilitates comprehensive assessment of network slice performance, predictive analysis, and dynamic optimization techniques to maintain good service quality despite fluctuations in operating conditions. Figure (2) shows the importance of features.

Network Slicing Simulation Environment and Methodology

The network slicing simulation was enhanced by incorporating additional components to more accurately represent real-time network situations. This was accomplished by the implementation of a comprehensive monitoring system utilizing four essential performance metrics. We utilized **Python** to create the simulation environment. We utilized **scikit-learn** for machine learning, **NumPy** for mathematical computations, and **matplotlib** to illustrate the program's performance. In the simulation design, many network slices representing different service categories with diverse QoS requirements and resource allocation patterns operate concurrently.

Simulation Architecture and Components

The multi-threaded simulation framework models network traffic over four network slices, each with capacity constraints ranging from 800,000 to 950,000 units. Each network slice has four nodes responsible for sending, receiving, and processing packets. Each slice functions on distinct ports (5000-5003) to maintain independent traffic management and use socket-based communication protocols to emulate data flow across a network. Simulations utilize realistic packet queuing with adjustable maximum queue sizes (10,000 packets) and artificial delay modifications to replicate the duration required for data transmission over a network.

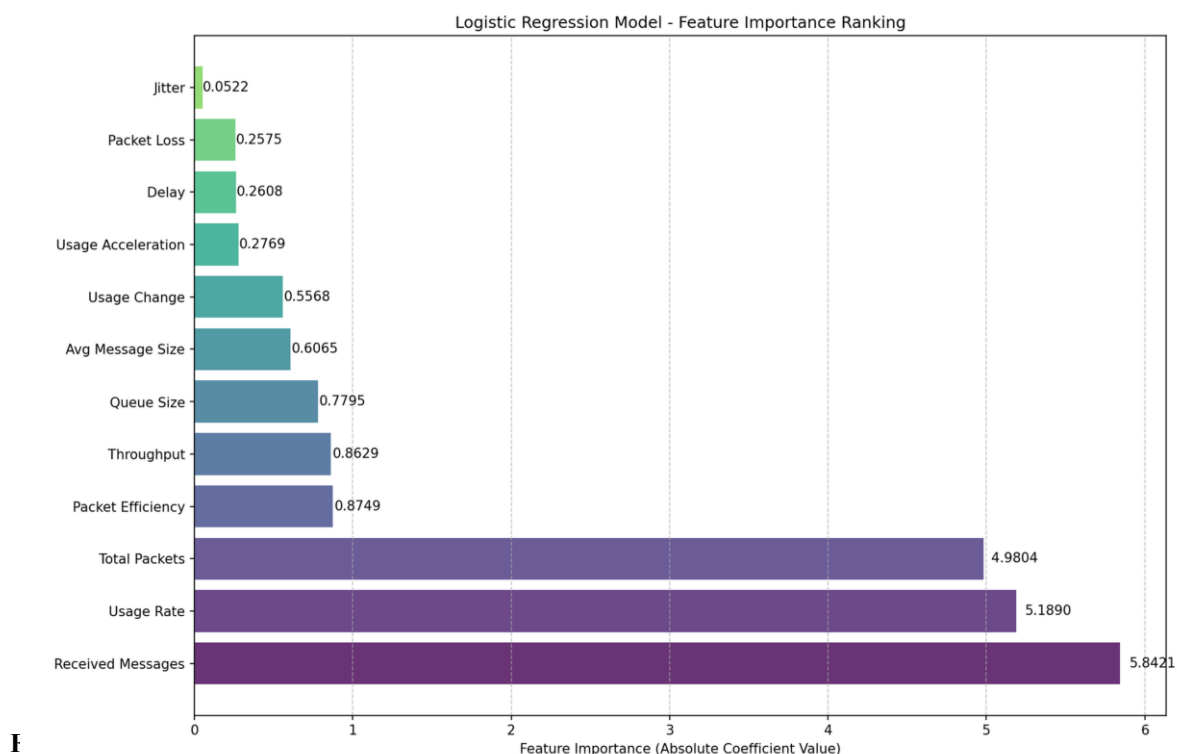


Figure (2) Feature Importance

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The simulation framework continuously monitors and computes twelve critical network performance metrics across four operational domains to deliver a comprehensive overview of the network's status. Metrics for resource utilization encompass usage rate measurements indicating current slice utilization as normalized capacity percentages (ranging from 0 to 1), temporal derivative calculations of resource consumption patterns to monitor changes in usage dynamics, and second-order derivative analysis for detecting usage acceleration, which reveals trend transitions and capacity stress points. In the second operational domain, quality of service parameters encompasses the assessment of packet loss through the percentage of packets discarded during transmission cycles, the evaluation of jitter via the statistical variance of packet delay distributions in milliseconds, the computation of average end-to-end packet transmission latency for delay evaluation, and the determination of packet efficiency ratios that quantify the percentage of successfully delivered packets. The third category of monitoring is queue management functions that monitor real-time packet buffer utilization by employing normalized queue size ratios (ranging from 0 to 1) and aggregating normalized total packet counts across specified time intervals to assess system congestion. The throughput characteristics of the fourth operational domain assess instantaneous data transmission rates in bytes per second, compute statistical means of transmitted packet sizes to ascertain average message size distributions, and tally successfully processed packets per measurement interval to quantify received message volumes. This comprehensive array of attributes, by examining multi-dimensional network performance, provides the necessary data structure for effective machine learning-driven overload prediction and dynamic resource allocation optimization in network slicing scenarios.

Simulation Parameters and Configuration

To make sure that the network behaves in a realistic way, the simulation works using carefully set parameters, Table (4) contains all those parameters.

Machine Learning Integration and Validation

The simulation employs the logistic regression classifier and the SVM model independently, utilizing L2 regularization for real-time overload prediction. The model employs class-balanced weighting and RandomOverSampler to address issues related to dataset imbalance. We employ SelectKBest feature selection to monitor shared information and retain the 10 most significant features. The training methodology employs 5x stratified validation and monitors performance across many intervals. ROC AUC analysis, precise recall curves, and the creation of a confusion matrix constitute comprehensive model evaluation focused on accuracy.

Table (4): Network Slicing Simulation Configuration Parameters

Parameter Category	Parameter Name	Value	Description
Temporal Parameters	Simulation Duration	60 seconds	Total continuous operation time
	Measurement Interval	0.1 seconds	Real-time monitoring frequency
	Model Update Frequency	10 seconds	Incremental learning intervals
	Thread Synchronization Timeout	0.1 seconds	Resource locking timeout
Network Configuration	Initial Slice Capacities	[800,000, 850,000, 900,000, 950,000] units	Per-slice initial capacity allocation
	Maximum Capacity Scaling	1,000,000 units per slice	Upper limit for dynamic scaling
	Buffer Sizes	262,144 bytes	Socket send/receive buffer size
	Queue Timeout	0.01 seconds	Non-blocking operation timeout
Traffic Generation	Message Size Distribution	Text: 20-50, Audio: 50-200, Video: 100-500 bytes	Content-based packet size ranges
	Load Factor Variation	0.2 to 0.8	Slice-dependent traffic intensity
	Artificial Delay Range	0.00001 to 0.00003 seconds	Realistic latency simulation bounds

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RESULT

In this section we present a comparison between the results of the two models used:

Packet delay results:

Experimental results show that the Logistic Regression model performed better at reducing packet delay compared to the SVM model across all network slices. The Logistic Regression model had an average overall delay of 3.01 ms, while the SVM model achieved an average delay of 3.30 ms, representing an 8.8% improvement for the Logistic Regression.

At the individual slice level, delay values in the Logistic Regression model ranged from 2.26 ms (slice 4) to 4.00 ms (slice 1), while in the SVM model they ranged from 2.45 ms to 4.25 ms for the corresponding slices. It is noted that both models followed a consistent pattern where the delay gradually decreased from the first to the fourth slice, reflecting the efficient distribution of loads across the different slices, Figure (3).

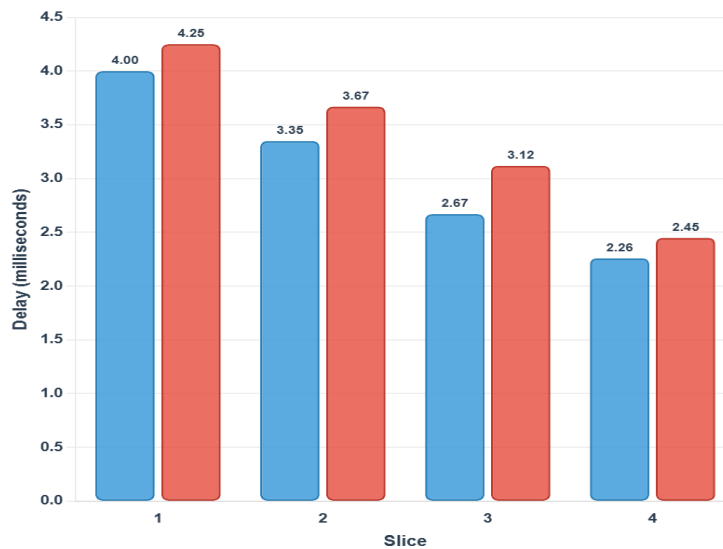


Figure (3) Comparison of Packet Delay Rate Using Logistic Regression and SVM

Jitter Results:

Jitter's comparison research shows that the SVM and Logistic Regression models perform slightly differently in the four network parts. The SVM model has a jitter range of 125.90 ms (slice 1) to 126.18 ms (slice 4). The Logistic Regression model, on the other hand, has a range of 116.65 ms (slice 2) to 123.49 ms (slice 4). The results reveal that the Logistic Regression model had more stable Jitter values than the SVM model, with a reduced standard deviation across different slices, figure (4).

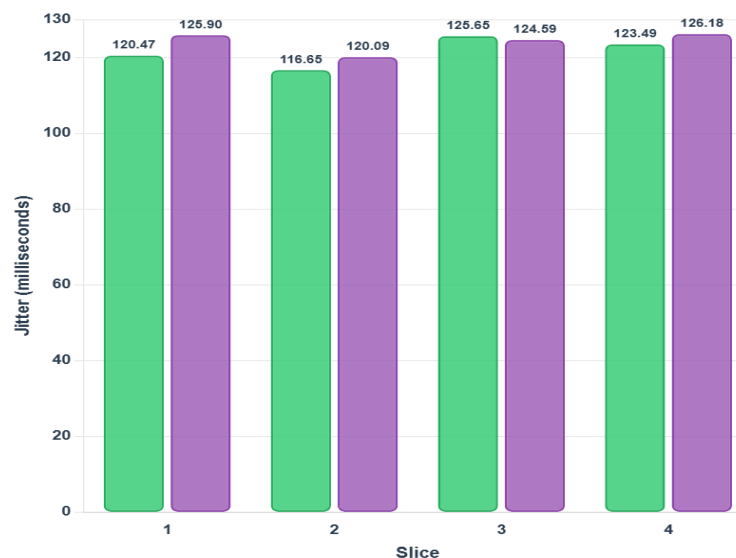


Figure (4) Jitter Rate Comparison Using Logistic Regression and SVM

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Throughput Results:

The Throughput measurement results demonstrate that the Logistic Regression model is clearly better than the SVM model in all network slices. The Logistic Regression model had a throughput of 95,394.27 bytes/second, which is 3.2% better than the SVM model's 92,393.85 bytes/second. The Logistic Regression model got higher scores in all slices: Slice 1 (16,839.04 vs. 16,223.93), Slice 2 (19,882.95 vs. 19,381.00), Slice 3 (25,117.01 vs. 24,079.55), and Slice 4 (33,555.27 vs. 32,709.37). The fourth slices had the maximum throughput in both models, which means that resources were used most efficiently in this slice. In both models, the throughput distribution goes up steadily from the first to the fourth slice. This shows that the load distribution strategies used were effective, figure (5).

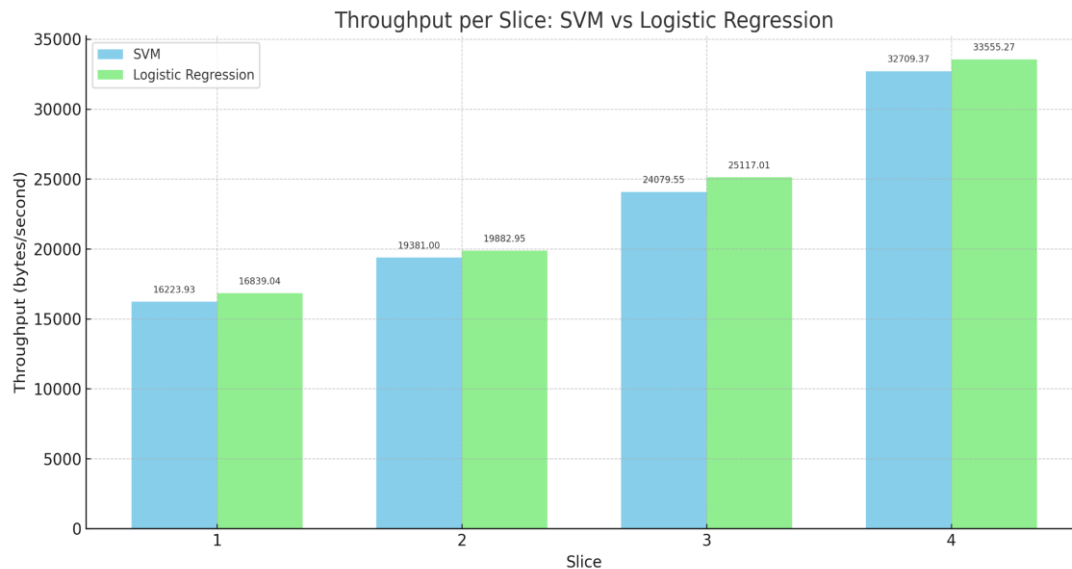


Figure (5) Throughput Comparison Using Logistic Regression and SVM

Why Logistic Regression is Better for Throughput and Delay while SVM is Better for Accuracy:

The contrasting outcomes of LR and SVM can be clarified by theoretical constructs like the bias–variance trade-off and the complexity–efficiency paradigm. Logistic Regression is a fundamental model characterized by higher bias and lower variance (Dubey et al., 2025). This indicates a reduced likelihood of overfitting and facilitates computation. These characteristics facilitate expedited forecasts and enhance network-level metrics such as throughput and delay, which are crucial for real-time decision-making. Conversely, SVM is a more complex model characterized by reduced bias and increased variance (Vidhya et al., 2025). This enables the identification of intricate patterns within the data, resulting in enhanced classification accuracy. However, more complexity necessitates greater computational power and results in slightly higher network latency. The identified trade-off suggests that LR is more suited for real-time resource allocation scenarios where latency and throughput are paramount, whereas SVM may be more beneficial in environments where accuracy is the primary goal.

Performance Summary:

SVM has greater classification accuracy (ROC AUC: 0.9999 vs. 0.9884), better validation accuracy (99.89% vs. 95.80%), and a more even distribution of feature importance.

Logistic Regression has a lot of benefits, such as better network performance (lower delay, higher throughput), more packet processing power, easier to understand, faster predictions in real time, and less chance of overfitting.

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Table (5): Comprehensive Performance Comparison - Logistic Regression vs SVM in Network Slicing

Performance Metric	Logistic Regression	SVM	Performance Analysis
Model Classification Performance			
ROC AUC Score	0.9884	0.9999	SVM Superior (+1.15%)
Optimal Threshold	0.5538	0.6284	SVM Higher Threshold
Validation Accuracy	95.80%	99.89%	SVM Superior (+4.09%)
Network Performance Metrics			
Total Packets Processed	104,348	101,163	Logistic Higher (+3.15%)
Overall Delivery Rate	100.00%	100.00%	Equal Performance
Average Network Delay	3.01 ms	3.30 ms	Logistic Better (-9.64%)
Total Network Throughput	95,394.27 B/s	92,393.85 B/s	Logistic Higher (+3.25%)
Slice-Level Performance Analysis			
Best Slice Throughput	33,555.27 B/s (Slice 4)	32,709.37 B/s (Slice 4)	Logistic Better (+2.59%)
Best Slice Delay	2.26 ms (Slice 4)	2.45 ms (Slice 4)	Logistic Better (-10.74%)
Average Jitter Range	116.65-125.65 ms	120.09-126.18 ms	Logistic Lower Variation
Packet Loss Rate	0.00% (All Slices)	0.00% (All Slices)	Equal Performance
Feature Importance Analysis			
Most Important Feature	Received Messages (5.8421)	Total Packets (0.3328)	Different Primary Predictors
Top 3 Features Concentration	78.0%	64.89%	SVM More Balanced
Feature Selection Method	SelectKBest + Mutual Info	SelectKBest	Logistic More Advanced

CONCLUSION

This research compares the most common machine learning approaches in network slicing for better resource management and allocation in contemporary network infrastructure. Machine learning approaches, including logistic regression and support vector machine (SVM) technologies, were employed to forecast overload in various network slices. This work's contribution is that it shows that Logistic Regression, even if it's simple, works very well for managing network slicing resources. This gives researchers and practitioners proof that they should choose LR as their first choice in comparable situations. This focus on network performance indicators instead of only accuracy fills an important gap in the literature and makes the study more useful in real life. The assessment of the network's performance yielded significant findings from simulation. The analysis revealed a jitter of 116.65 ms with logistic regression and 120.09 ms with SVM. Throughput demonstrated notable improvement, with slice 4 in the logistic regression network achieving a peak of 33555.27 B/s, whereas slice 4 in the SVM network recorded 32709.37 B/s. The findings revealed a latency of 2.26 ms in slice 4 for the network employing logistic regression, contrasted with a delay of 2.45 ms in the network utilizing SVM. The results demonstrate the efficacy of the machine learning system in resource allocation, and a thorough comparison reveals the advancement of the logistic regression model and its proficiency in categorizing and predicting network congestion. The logistic regression model achieved a validation accuracy of 95.80%, but the SVM model attained a validation accuracy of 99.89% utilizing the identical dataset for both models. Future study could enhance the route comparison framework by integrating sophisticated machine learning methodologies, including deep reinforcement learning, neural networks, and random forests. This will improve our capacity to allocate resources at the slice level in response to various traffic kinds. Future intelligent and adaptive research may enhance recommendations by broadening the study's scope to incorporate novel approaches.

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