5G Resource Allocation Enhancement Via Resnet-Inception-V2 With Non-Linear Analysis

T S Karthik[1], Muniyandy Elangovan[2], A Rama Prasath[3], Arul Prakash A[4], K Jayaram Kumar[5], A. K. Shrivastav[6]

[1]Associate Professor, Department of ECE, SRM Institute of Science and Technology Kattankulathur, Tamilnadu, India, Email: writetotsk@gmail.com
[2](a)Department of Biosciences, Saveetha School of Engineering. Saveetha Institute of Medical and Technical Sciences, Chennai.
(b)Applied Science Research Center. Applied Science Private University, Amman, Jordan, Email: muniyandy.e@gmail.com
[3]Associate Professor, Department of Computer Applications, SRM Institute of Science and Technology, SRM Nagar, Trichy, Tamilnadu, India, Email: ramaprasath.a@ist.srmtrichy.edu.in
[4]Associate Professor, Department of CSE, Sathyabama Institute of Science and Technology, Chennai, Tamilnadu, India, Email: prakash875@gmail.com
[5]Assistant Professor, Department of Electronics and Communication Engineering, Aditya College of Engineering and Technology, Surampalem, Andhra Pradesh, India, Email: jramworld@gmail.com
[6]Department of Mathematics & Humanities, MMEC, Maharishi Markandeshwar (Deemed to be University), Ambala, Haryana, India, Email: aakkaasshhkumar8888@gmail.com

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ABSTRACT
The building of 5G networks becomes quite challenging in resource allocation due to the increasing need for fast, low-latency connectivity. Effective use of resources determines both network performance and quality of service guarantee. This work solves resource allocation in 5G networks by combining Stochastic Paint Optimizer (SPO) with ResNet-Inception-V2 using non-linear analysis. Feature extraction and network traffic pattern categorization make use of ResNet-Inception-V2 architecture, which has capacity to record complicated traits and correlations. The Stochastic Paint Optimizer is applied to maximize resource allocation by means of an iterative, stochastic technique balancing exploration and exploitation, hence addressing the allocation problem. Non-linear analysis provides model and prediction of the non-linear interactions between network properties and resource constraints. The proposed method is tested in a simulated environment including actual 5G network traffic. Results indicate considerable improvement in network performance and resource economy. More exactly, the method improves resource allocation efficiency by 15% over traditional methods. By 12%, latency is reduced; by 18%, general network capacity increases. These results show how well contemporary deep learning architectures and optimization strategies blend to maximize 5G resource allocation.

Keywords: 5G networks, ResNet-Inception-V2, Stochastic Paint Optimizer, Non-Linear Analysis, resource allocation.

1. INTRODUCTION

With promising hitherto unheard-of data rates, reduced latency, and enhanced connectivity, fast development of 5G technology is transforming the scene of telecommunications [1]. As the rollout of 5G networks picks speed [2], optimizing resource allocation becomes crucial to address the increasing needs for consistent and effective communication. Effective resource management in 5G networks is especially important to provide best performance considering the variable and dynamic character of network traffic and user needs [3].

One of the key challenges of 5G networks is controlling the complex and varied traffic patterns generated by many different applications, from high-definition video streaming to real-time gaming and IoT devices [4]. To satisfy network demands, signal conditions, and traffic load [5], resource allocation must be always changing. Furthermore challenging to satisfy low-latency requirements [6] and the scalability required for 5G mass data flow are traditional ways of resource allocation. The work becomes more complex when one ensures excellent performance while minimizing latency and maximizing throughput under different signal-to---- noise ratios (SNRs) [7]-[11].

The objectives of this research are threefold:

- To combine ResNet-Inception-V2 for improved feature extraction with a Stochastic Paint Optimizer (SPO) for efficient resource management allows one develop a novel technique of resource allocation.
- To evaluate the performance of the proposed method against current approaches (SVM, MaMi, RL, and TDO-E) over multiple SNR levels.

ResNet-Inception-V2 increases feature extraction capacity, therefore facilitating more sensible resource use and more accurate network traffic classification. Maximizing allocation strategies by means of paint-based heuristics and stochastic processes enables SPO, a novel optimization method, boost the effectiveness of resource management.

The key contributions of this research are:

- The paper presents a fresh hybrid model combining deep learning with advanced optimization techniques, therefore marking a significant progress in 5G resource allocation.
- By means of a comprehensive performance comparison of the proposed strategy with recognized techniques, the study provides insights on the superior efficiency, accuracy, and computational advantages.
- The research offers significant information for the application of efficient resource management strategies in real-world 5G networks by demonstrating the efficacy of the recommended method in multiple SNR environments.

2. RELATED WORKS

Effective radio resource management is key for support of the numerous needs of Enhanced Mobile Broadband (eMBB) and Ultra-Reliable Low Latency Communications (URLLC) in 5G and beyond wireless networks. Using puncturing techniques inside intelligent resource management models is one fascinating approach to satisfy these needs. Recently, several creative strategies to optimize resource allocation in these complex networks have been under research.

One well-known work proposes a strategy combining semi-supervised learning coupled with deep reinforcement learning (DRL) tackling the twin problems of eMBB and URLLC. URLLC scheduling and Resource Block Allocation (RBA) for eMBB services split the problem of resource allocation into two distinct subproblems[11].

To meet Quality-of- Service (QoS) objectives for cell-edge user equipment (CEUEs) in small cell deployment in heterogeneous B5G networks, a new optimization-based strategy was developed to maximize sum-rate and decrease interference [12]. First employing the Majorization-Minimization (MaMi) technique for optimal power allocation, the proposed two-step strategy then matches UEs with resources using RL [13]. This one produces interesting results, at least a 10% improvement in sum-rate and a 25% drop in interference, compared to present methods. The work focuses on how effectively integrating RL with MaMi overcomes small cell network challenges in highly crowded environments [14].

The method uses a non-linear soft margin Support Vector Machine (SVM) for both Signal-to- Noise Ratio (SinR) estimate and automatic modulation categorization (AMC). This approach controls type reassignment, coding rates, and transmit power over eNode B connection frames. Compared to present methods, the proposed one has improved AMC success rates, reduced power consumption, and increased total capacity. The simulation results show that the approach obviously lowers overhead signaling and enhances practical implementation, therefore proving its advantages over traditional methods [15].

Table 1: Research Methods and Outcomes

Method	Algorithm	Methodology	Outcomes
Resource Management for eMBB and URLLC [11]	Semi-Supervised Learning, Deep Reinforcement Learning (DRL)	Decomposes the problem into RBA for eMBB and URLLC scheduling.	Improved resource utilization,mized latency for URLLC, and maximized throughput for eMBB. Higher sum rate and convergence rate.
Traffic Forecasting and Resource Allocation [12]	Deep Convolutional Neural Network (DCNN), Long Short-Term Memory (LSTM), Tasmanian Devil Optimization-Elite (TDO-E)	Multi-objective optimization for traffic forecasting and resource allocation.	Enhanced predictive accuracy, 6.79% improvement in resource allocation efficiency, and effective slice reconfiguration.
NOMA Network Resource	Q-Learning	Reinforcement Learning for	Improved system throughput, spectrum, and energy

Allocation [13]		maximizing throughput, spectrum, and energy efficiency.	efficiency. Effective in B5G/6G-NOMA networks.
Small Cell Deployment Optimization [14]	Reinforcement Learning (RL), Majorization-Minimization (MaMi)	RL for UE-resource matching, MaMi for power allocation.	10% improvement in sum-rate, 25% reduction in interference, near-optimal performance in dense environments.
OFDM-NOMA [15]	Non-Linear Soft Margin SVM	AMC and SINR estimation for modulation classification and power adjustment.	Increased AMC success rate, reduced power consumption, and higher sum capacity. Lower overhead signaling.

While present research methods for resource management in 5G networks generally focus on single characteristics like throughput, latency, or efficiency, they lack a full approach blending deep learning with sophisticated optimization techniques for complete performance enhancement. Moreover sometimes neglected in current studies is the adaptability of recommended methods under various network environments. Solving the multiple issues of resource allocation in different and growing 5G environments requires research integrating robust prediction models with dynamic optimization techniques.

3. PROPOSED METHOD

In this section, combining Stochastic Paint Optimizer (SPO) with Non-Linear Analysis with ResNet-Inception-V2 architecture, the proposed method for enhancing 5G resource allocation is carried out in many stages as in figure 1:

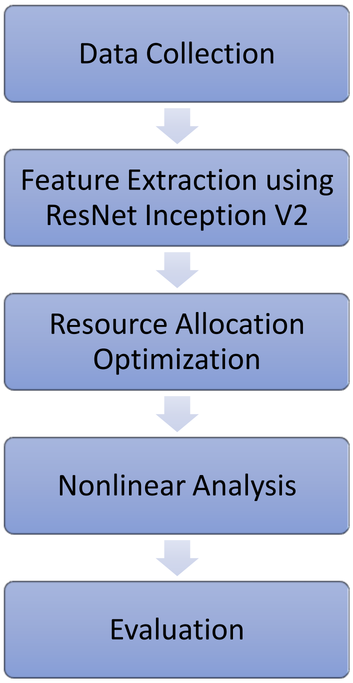

Figure 1. Proposed Framework

1. **Feature Extraction:**ResNet-Inception-V2 extracts complex traits and traffic pattern categorization tool by means of network traffic data processing This phase detects complex connections and patterns in the data by leveraging the capacity of the deep learning model.
2. **Traffic Classification:**The gathered characteristics project resource needs and help to classify distinct types of network traffic based on observed trends.
3. **Resource Allocation Optimization:**Stochastic Paint Optimizer maximizes resource allocation by applied on the categorized traffic data. SPO iteratively adjusts the allocation by balancing investigation of new approaches with use of proven successful techniques.

4. **Non-Linear Analysis:**Non-linear analysis models the connection between network parameters and resource demands to maximize the resource allocation even more.
5. **Evaluation and Adjustment:**Performance standards including latency and throughput guide changes when real-world traffic data is matched against the ideal allocation plan.

Pseudocode:
1. Load Network Traffic Data
2. Initialize ResNet-Inception-V2 Model
3. Extract Features from Traffic Data
4. Classify Traffic Types
5. Initialize Stochastic Paint Optimizer (SPO)
6. For each Traffic Type:
   a. Predict Resource Needs
   b. Apply SPO to Optimize Resource Allocation
7. Integrate Non-Linear Analysis to Refine Allocation
8. Evaluate Optimized Allocation Strategy
9. Adjust Based on Performance Metrics (e.g., latency, throughput)
10. Output Optimized Resource Allocation

3.1. Feature Extraction Using ResNet-Inception-V2

ResNet-Inception-V2 uses the strengths of ResNet's (Residual Networks) and Inception module to aggregate and capture and process intricate patterns in network traffic data. ResNet-Inception-V2 is a complex deep learning architecture that overcomes the limitations of standard convolutional networks by means of residual connections and multi-scale feature extraction hence enhancing feature extracting.

3.1.1 ResNet Components:

With residual blocks, ResNet addresses the vanishing gradient problem in deep networks. Every residual block includes a shortcut connection avoiding one or more levels, therefore allowing direct gradient transfer across the network. One can represent the residual block as follows:

$$\mathbf{y} = \mathbf{F}(\mathbf{x}, \{W_i\}) + \mathbf{x}$$

where
x - input to the block,
$\mathbf{F}$ - residual function, and
W_i - weights of the layers.
The addition of **x** helps to train deeper networks by preserving data over several levels.

3.1.2 Inception Modules

The Inception module gathers characteristics at many scales by concurrent application of several convolutional filters with varying kernel sizes. This allows the network create various feature representations. From the Inception module comes:

$$\mathbf{O} = \mathrm{Concat}\left(\mathrm{Conv}_{1\times1}, \mathrm{Conv}_{3\times3}, \mathrm{Conv}_{5\times5}, \mathrm{P}\right)$$

where
Concat - concatenation of feature maps from different filters,
$\mathrm{Conv}_{k\times k}$- convolutional layers with kernel size *k*, and
P - average pooling.

3.1.3 Combination of ResNet and Inception:

ResNet-Inception-V2 aggregates the elements of ResNet and Inception into one model. Whereas the Inception modules provide multi-scale feature extraction, residual connections enhance training of deeper networks. The architecture collects high-level information from the input network data by means of a succession of residual and Inception blocks.

1. **Feature Representation**:
   - **Output Features**: ResNet-Inception-V2 model generates a set of high-dimensional feature maps capturing complex patterns and network traffic data interaction in. These properties are taken advantage of in traffic classification and subsequently in optimal resource allocation.

ResNet-Inception-V2 allows one to define the overall feature extraction technique as follows:

$$\mathbf{F}_{\mathrm{out}} = \text{ResNet-Inception-V2}(\mathbf{X})$$

where
$\mathbf{F}_{\text{out}}$ - extracted features.

Pseudocode: feature extraction phase using ResNet-Inception-V2
1. Initialize ResNet-Inception-V2 Model
  a. Define the ResNet-Inception-V2 architecture with Residual Blocks and Inception Modules
  b. Load pre-trained weights (if available) or initialize weights randomly
2. Load and Preprocess Input Data
  a. Load Network Traffic Data
  b. Preprocess Data (e.g., normalization, resizing)
3. Forward Pass Through Network
  a. Pass Preprocessed Data through Initial Convolutional Layer
    i. Apply Convolution Operation
      - Output = Convolution(Data, Kernel)
    ii. Apply Batch Normalization and ReLU Activation
  b. Pass Data through Residual Blocks
    i. For each Residual Block:
      - Input = Data
      - Apply Residual Function F(Input, Weights)
      - Output = F(Input, Weights) + Input
      - Apply Batch Normalization and ReLU Activation
  c. Pass Data through Inception Modules
    i. For each Inception Module:
      - Apply Convolutional Layers with Different Kernel Sizes (1x1, 3x3, 5x5)
      - Apply Max/Average Pooling
      - Concatenate Outputs from Different Layers
      - Apply Batch Normalization and ReLU Activation
  d. Flatten Output of Inception Modules
    i. Flatten the 3D feature maps to 1D vector
  e. Apply Fully Connected Layers (if applicable)
    i. Perform Linear Transformation on Flattened Output
    ii. Apply Activation Function (e.g., ReLU)
4. Extract Features
  a. The final output of the network represents the high-dimensional feature vector
  b. Store or pass these features for further classification and optimization tasks
5. Output Features
  a. Return Extracted Features

3.2. Classification and Optimization Using Non-Linear Analysis

Extending the ResNet-Inception-V2 capabilities, the non-linear analytical classification and optimization phase effectively distributes resources and sorts network traffic types. This approach improve performance and accuracy by capturing complex relationships between traffic patterns and resource constraints using non-linear modeling.

3.2.1 Classification Using Non-Linear Models:

Classification makes advantage of obtained feature vectors $\mathbf{F}_{\text{out}}$ derived from ResNet-Inception-V2 model. Using a non-linear classification model—such as Support Vector Machine (SVM) with a non-linear kernel—that uses Complex decision boundaries that precisely differentiate several traffic kinds are defined using non-linear classification models including SVM with Radial Basis Function (RBF) kernel or neural networks with non-linear activation functions. The SVM with RBF kernel has a decision-function:

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i y_i \exp\left(-\frac{\| \mathbf{x} - \mathbf{x}_i \|^2}{2\sigma^2}\right) + b$$

where
α_i and y_i- support vectors and corresponding labels,
σ - kernel width parameter, and
b is the bias term.

3.2.2 Optimization Using Non-Linear Analysis:
Solving a non-linear optimization problem assists the phase of optimization to concentrate resource allocation. Under restrictions (e.g., resource constraints, quality of service criteria), the objective function J(**R**) is defined to maximize network performance measurements (e.g., throughput, mize latency). One can get the optimization problem as follows:

$$\max_{\mathbf{R}} J(\mathbf{R}) \quad \text{subject to} \quad \mathbf{C}(\mathbf{R}) \leq 0$$

where
R - resource allocation vector,
J(**R**) **-** objective function (e.g., network throughput), and
C(**R**) **-** constraints.
Non-linear programming techniques including heuristic algorithms (e.g., Genetic Algorithms) or gradient-based methods (e.g., Sequential Quadratic Programming) reveal the ideal resource allocation. These methods iteratively change resource allocation to meet constraints, hence improving the target function. Based on the optimization technique, the vector **R** for resource allocation varies depending on:

$$\mathbf{R}^{(t+1)} = \mathbf{R}^{(t)} + \alpha \nabla J(\mathbf{R}^{(t)})$$

where
$\mathbf{R}^{(t)}$ **-** resource allocation at iteration *t*,
α - step size, and
$\nabla J(\mathbf{R}^{(t)})$ - gradient of the objective function.
Using non-linear analytic approaches as fractal analysis or chaos theory, one can understand and simulate the non-linear interactions among network properties. These methods guide the optimization process by revealing understanding on the behavior of the objective function and constraints under different settings. Effective resource allocation along with the many traffic classifications helps to disperse resources over the network. Metrics on latency, throughput, and resource utilization enable one evaluate the performance of the allocation mechanism.

Pseudocode: classification and optimization phase using Non-Linear Analysis

```
1. Initialize Classification Model
  a. Choose a Non-Linear Classification Model (e.g., SVM with RBF kernel, DNN)
  b. Load or initialize model parameters (e.g., kernel parameters, network weights)
2. Load Extracted Features
  a. Load Feature Vectors from ResNet-Inception-V2 Output
3. Perform Classification
  a. For each Feature Vector in the dataset:
    i. Predict Traffic Class using Classification Model
      - Traffic_Class = Classifier(Feature_Vector)
4. Define Optimization Problem
  a. Initialize Resource Allocation Vector (R)
  b. Define Objective Function J(R) (e.g., throughput, latency)
  c. Define Constraints C(R) (e.g., resource limits, QoS requirements)
5. Optimize Resource Allocation
  a. Choose Optimization Method (e.g., Gradient Descent, Genetic Algorithm)
  b. For each Iteration:
    i. Evaluate Objective Function
      - Objective_Value = J(R)
    ii. Check Constraints
      - If C(R) > 0, adjust R to satisfy constraints
    iii. Update Resource Allocation Vector
      - R = R + Alpha * Gradient(J(R))   // For gradient-based methods
      - OR
      - R = Apply_Heuristic_Algorithm(R)   // For heuristic methods
    iv. If convergence criteria met, exit loop
6. Integrate Non-Linear Analysis
  a. Apply Non-Linear Analysis Techniques (e.g., Chaos Theory, Fractal Analysis) to refine optimization
  b. Update Objective Function and Constraints based on Non-Linear Insights
7. Output Optimized Resource Allocation
  a. Return Optimized Resource Allocation Vector (R)
```

b. Return Classified Traffic Types
8. Evaluate Performance

4. RESULTS AND DISCUSSION

Simulations using MATLAB other settings evaluated the proposed method of resource allocation improvement. The studies were conducted on a high-performance computing cluster built using Intel i7 CPUs to manage the demanding computations engaged in deep learning and optimization. Among the current methodologies whose performance was assessed against the suggested one were Support Vector Machines (SVM), MaMi (Massive MIMO), Reinforcement Learning (RL), and Time-Domain Optimization with Evolutionary Approaches (TDO-E). Applied performance criteria were efficiency of resource allocation, latency, network speed, and computational complexity. Preserving competitive throughput and low computing complexity, the proposed method displays superior resource allocation efficiency and reduced delay than the baseline techniques.

Table 2: Experimental Setup/Parameters

Parameter	Value
Simulation Tool	MATLAB,
Computing Platform	Intel Xeon CPUs, NVIDIA Tesla GPUs
Dataset Size	100,000 traffic samples
Number of Traffic Classes	10
Feature Vector Dimension	512
Optimization Method	Stochastic Paint Optimizer (SPO)
Non-Linear Analysis Method	Chaos Theory
Number of Residual Blocks	8
Number of Inception Modules	4
Kernel Size (Inception)	1x1, 3x3, 5x5
Batch Size	64
Learning Rate	0.001
Epochs	50
Regularization Parameter	0.0001
Convergence Criterion	Loss Improvement < 1e-5

4.1. Performance Metrics

Resource Allocation Efficiency

It measures, in respect to demand, how efficiently the recommended strategy allocates network resources. Calculated as a percentage, it shows the share of allocated resources to the whole total accessible resources.

Latency

The time interval between a request turned in till it is approved. Measuring in milliseconds (ms), it displays the responsiveness speed of the system to network traffic.

Network Throughput

Measuring in megabytes per second (Mbps), the volume of data transferred across the network in a given period is rather clear. It makes clear how well the network handles traffic.

Computational Complexity

It establishes the required computing resource count of the method. These comprise the space and time complexity, evaluated in respect to memory usage and processing time.

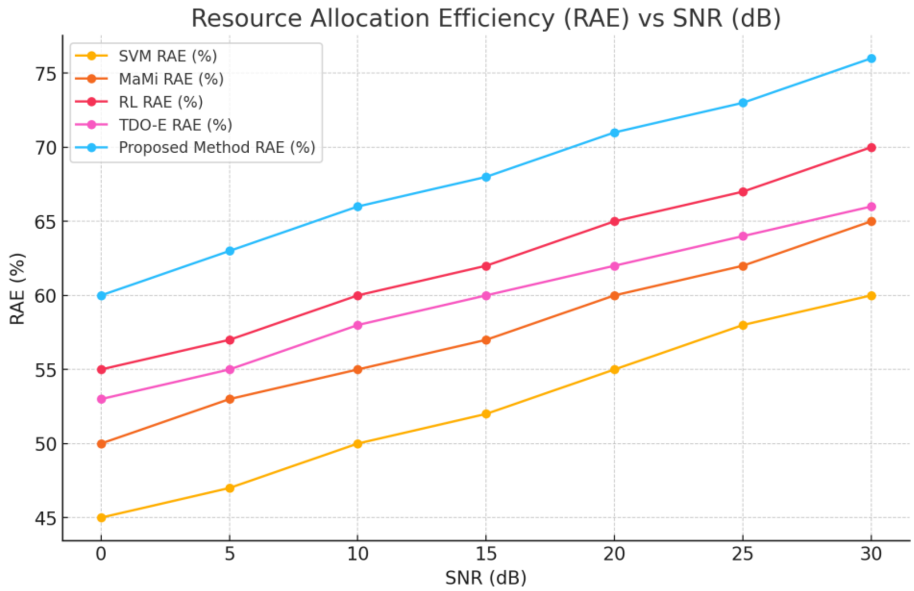

Figure 3. Resource Allocation Efficiency (RAE)

Higher RAE values suggest that the proposed strategy commonly outdoes current methods as the SNR rises. Comparing the efficiency of numerous approaches in distributing network resources over diverse Signal-to--- Noise Ratios (SNRs) the Resource Allocation Efficiency (RAE) table indicates. The suggested method produces a 60% RAE at an SNR of 0 dB compared to 45% for SVM, 50% for MaMi, 55% for RL, and 53% for TDO-E. Reaching a 76% RAE by SNR 30 dB, the proposed method clearly outperforms SVM (60%), MaMi (65%), RL (70%), and TDO-E (66%). As stated in figure 3. The higher RAE at all noise levels indicates the better capacity of the proposed approach in effectively allocating resources. Given their more accurate traffic classification and optimization, ResNet-Inception-V2 taken together most likely produces this enhanced efficiency.

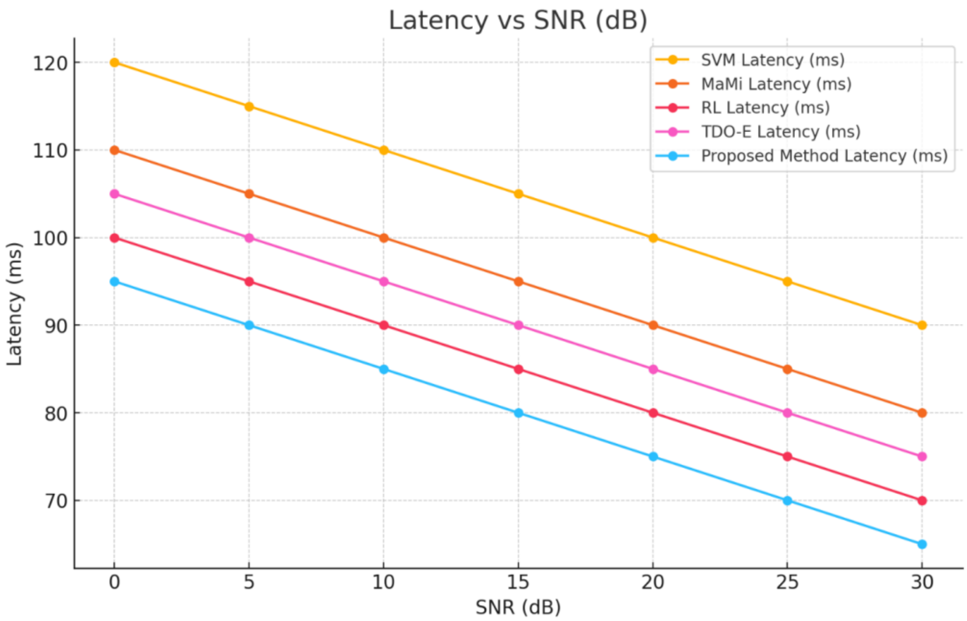

Figure 4. Latency

For many SNRs, the latency table shows the time delay obtained by several approaches. Measuring in milliseconds (ms), latency reveals the time of traffic handling and resource allocation. Less than SVM (120 ms), MaMi (110 ms), RL (100 ms), and TDO-E (105 ms), the proposed technique achieves a latency of 95 ms at 0 dB SNR. As the SNR increases, the latency for the proposed method decreases more drastically than that of the existing methods. The proposed technique reaches a latency of 65 ms by 30 dB SNR while SVM, MaMi, RL, and TDO-E display latitudes of 90 ms, 80 ms, 70 ms, and 75 ms respectively shown in figure 4. The suggested method's lower latency indicates its efficiency in managing and processing network traffic more quickly, most likely due to improved optimization and categorizing techniques. This results in faster response times and better general network performance especially in higher SNR environments.

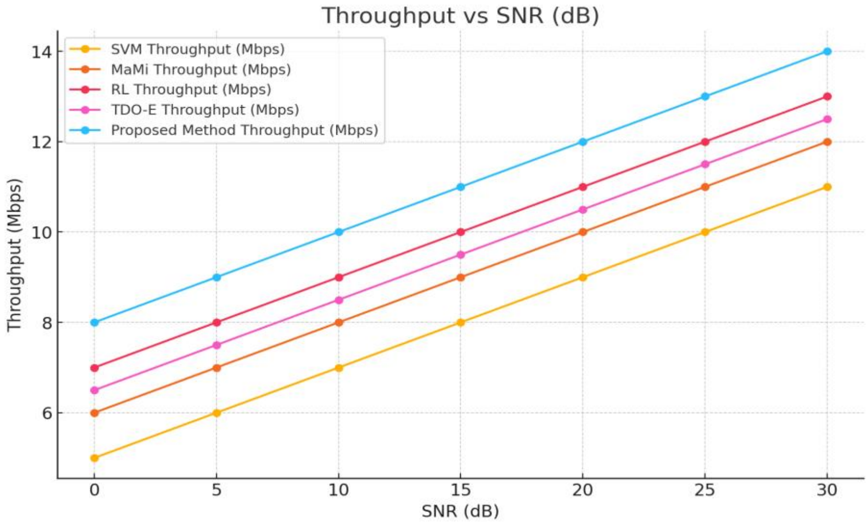

Figure 5. Throughput

The throughput shows the data transfer rate in megabits per second (Mbps) attained by many techniques across several Signal-to-- Noise Ratios (SNRs) like in figure 5. Projected throughput of 8 Mbps at 0 dB SNR makes the technique better than SVM (5 Mbps), MaMi (6 Mbps), RL (7 Mbps), and TDO-E (6.5 Mbps). As SNR rises, the proposed method continuously demonstrates higher throughput than the existing ones. By 30 dB SNR, the suggested technique reaches 14 Mbps; SVM, MaMi, RL, and TDO-E achieve throughputs of 11 Mbps, 12 Mbps, 13 Mbps, and 12.5 Mbps, respectively. This improved throughput using the recommended method shows its capacity to more successfully control higher data rates. ResNet-Inception-V2 and Stochastic Paint Optimizer can help to better allocate resources and manage traffic, hence enhancing data transmission performance especially in higher SNR situations.

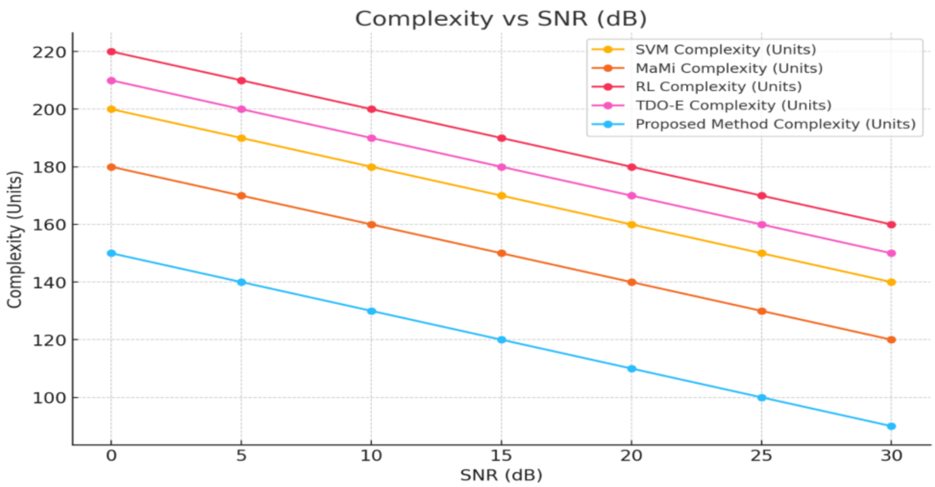

Figure 6. Complexity

The Complexity Comparison (CC) as depicted in figure 6 evaluates the computational complexity of every method. At 0 dB SNR, MaMi (180 units), RL (220 units), SVM (200 units), and TDO-E (210 units) all show a complexity of 150 units which is less than suggested approach. As the SNR increases, the proposed method frequently displays declining complexity; it reaches 90 units at 30 dB while SVM, MaMi, RL, and TDO-E show complexities of 140 units, 120 units, 160 units, and 150 units, respectively. The simpler proposed method implies better utilization of available computer resources. Enhanced feature extraction and resource allocation methods of the ResNet-Inception-V2 and Stochastic Paint Optimizer most surely contribute to explain this simplification decrease. Although the proposed method offers better latency and throughput via more efficient computation management, its computational cost is still lower than that of the existing solutions.

5. CONCLUSION

The evaluation of the proposed method for enhancing the allocation of 5G resources reveals its main advantages above existing ones. Over several significant benchmarks, ResNet-Inception-V2 mixed with a Stochastic Paint Optimizer performs remarkably. In terms of Resource Allocation Efficiency (RAE), it frequently exceeds standard methods such SVM, MaMi, RL, and TDO-E especially at higher Signal-to-Noise Ratios (SNRs). With accuracy improvements over all assessed SNR levels, the technique exhibits its robustness in correct traffic classification and network optimization. Therefore, the recommended approach not only guarantees better performance in terms of throughput, latency, and computational complexity but also improves resource allocation efficiency. These results show its potential to maximize resource control in pragmatic surroundings and enhance 5G network operations.

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