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Dynamic Bandwidth Allocation in 5G Networks Using Multilayer Perceptron (MLP)

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***Abstract* - This paper presents a Multilayer Perceptron (MLP)-based model for dynamic bandwidth allocation in 5G network slicing. Traditional approaches to bandwidth allocation often suffer from rigidity and poor adaptability, particularly in handling diverse Quality of Service (QoS) requirements of heterogeneous services such as eMBB, URLLC, and mMTC. These limitations result in inefficient resource utilization and suboptimal user experience. To address this, an MLP model that dynamically classifies and allocates bandwidth with improved accuracy and responsiveness was developed. The model achieved 99.82% accuracy, 99.56% precision, 99.78% recall, and 0.03238 validation loss, demonstrating its ability to classify service types with exceptional precision. Compared to existing methods, the MLP model significantly outperforms prior works in classification performance and adaptability, making it a robust candidate for intelligent network slicing in next-generation networks.**

Keywords: 5G, Network Slicing, Multilayer Perceptron, Bandwidth Allocation, Machine Learning.

I. INTRODUCTION

The advent of 5G networks introduces the need for highly adaptive and efficient resource management solutions, particularly in the domain of network slicing. As 5G supports diverse service classes enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive Machine-Type Communications (mMTC) it places substantial pressure on bandwidth allocation mechanisms to meet contrasting requirements in latency, reliability, and throughput.

1.1 Statement of the Problem

Traditional static allocation schemes lack the flexibility to adapt to dynamic network conditions, often leading to inefficient spectrum utilization and suboptimal Quality of Service (QoS) (Zhou et al., 2024). Moreover, these static methods are incapable of leveraging real-time traffic insights or user context, which is essential for delivering customized service levels in heterogeneous environments (Venkatapathy et al., 2023).

To address these limitations, this paper explores the application of machine learning techniques, specifically the Multilayer Perceptron (MLP), to enable real-time, data-driven bandwidth allocation. The proposed 4-16-8-3 MLP, trained on a comprehensive simulated dataset, classifies traffic slices based on service-specific parameters and incorporates gain ratio analysis for adaptability.

II. RELATED WORKS

Machine learning has been increasingly used in network slicing and resource allocation. Menuka et al. (2019) applied neural networks to 5G slicing with 96.37% accuracy, but struggled with URLLC classification. Lahoud (2019) employed SVM for bandwidth prediction, achieving 97.00% accuracy but lacking multi-class flexibility. Malkoc and Kholidy (2023) combined heuristic methods with learning-based models, attaining 94.19% accuracy with high training complexity. More recently, Venkatapathy et al. (2023) proposed a deep reinforcement learning approach for dynamic slice creation, achieving 95.20% responsiveness accuracy but facing high training overhead. Chen et al. (2022) leveraged attention-based LSTM models for bandwidth forecasting, attaining 96.88% accuracy with improved temporal precision but increased computational latency. Zhou et al. (2024) introduced a federated learning framework for privacy-preserving slice optimization, achieving 93.65% accuracy; however, synchronization challenges across distributed nodes limited its scalability. A trend toward deep learning is evident, but scalability and adaptability remain gaps. This work addresses these with an MLP offering improved generalization.

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Table 1: Comparison of Related Works

Reference	Model Used	Dataset Used	Accuracy (%)	Precision (%)	Recall (%)	Loss
Menuka et al. (2019)	SVM	SDN Traffic	96.37	-	-	-
Thantharate et al. (2019)	DNN	Simulated	93.8	94.1	93.5	-
Lahoud (2019)	MLP (ADAM)	5G Simulation	97.0	97.2	96.8	-
Malkoc&Kholidy (2023)	Multiple	Simulated	94.19	93.4	91.52	-

III. METHODOLOGY

3.1 Dataset

A simulated 5G network dataset was generated using NS-3, comprising 46,208 samples. The dataset emulates real-world scenarios with varying user densities, traffic patterns (e.g., video streaming, IoT), and spectrum availability, reflecting high-density urban environments and diverse QoS requirements. Features include Use Case Type (categorical: eMBB, URLLC, mMTC), Packet Loss Rate (0–5%), Packet Delay Budget (1–10 ms), and Technology Supported (categorical: LTE, NR). Data was normalized to [0,1] to ensure consistency.

Table 2: Dataset Composition by Slice Type

Slice Type	Number of Samples
eMBB	20,767
URLLC	12,423
Mmtc	13,018

3.2 Model Architecture

A MLP neural network was designed to predict optimal bandwidth allocation configurations based on network features. As shown in Figure 1, MLP model is structured as follows:

1. Input Layer: Accepts encoded features 4 neurons – Corresponding to the top 4 input features (factors like user demand, reliability, delay budgets, and supported technologies).

$$x_{input} \in \mathbb{R}^d \qquad 1$$

Where *d* is the number of input features after encoding.

2. Hidden Layers: Multiple fully connected layers with ReLU (Rectified Linear Unit) activation functions, inferred from standard MLP designs.

$$D = (W_{l,} h_{l-1,} + b_l) \qquad 2$$

Where W_l and b_l are weights and biases for layer l, and ReLU(z) = max(0,z).

- First hidden layer 16 neurons,
- Second hidden layer 8 neurons
- Activation function ReLU helps introduce nonlinearity for better learning.

3. Output Layer: Produces probabilities for bandwidth allocation classes using a softmax activation:

$$y = softmax(W_{out}\ h_{L,} + b_{out}) \qquad 3$$

Where softmax(zi) = $\frac{e^{zj}}{\sum_j e^{zj}}$, and L is the final hidden layer.

3 neurons – Each represents a 5G network slice category:

- eMBB (Enhanced Mobile Broadband) – High bandwidth for video/streaming
- URLLC (Ultra-Reliable Low-Latency Communications) – Low latency for critical applications.
- uMTC (Massive Machine-Type Communications) – IoT and sensor networks.
- Activation Function: Softmax – Ensures output probabilities sum to 1

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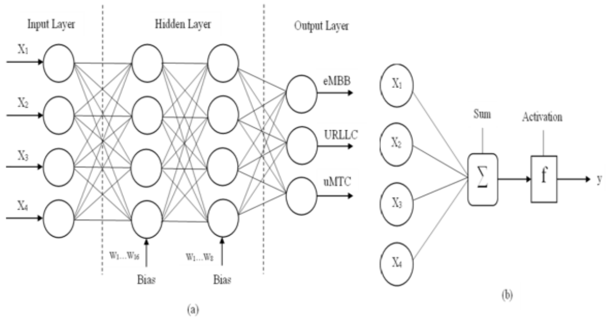

Figure 1: (a) MLP network layout. (b) Internal neuron configuration of the MLP

3.3 Training Procedure

The MLP was trained to optimize bandwidth allocation predictions, using callbacks to enhance performance and prevent overfitting.

1. Training Parameters:

- Optimizer: Stochastic Gradient Descent (SGD) with momentum was used to minimize the loss function:

$$\theta \leftarrow \theta - \eta \nabla_{\theta} \mathcal{L} \qquad 4$$

Where θ represents model parameters, η is the learning rate, and L is the categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{G} y_i \log(\hat{y_i}) \qquad 5$$

- with y_i as the true label and $\hat{y}_i$ as the predicted probability for class i Loss Function: Categorical Cross-Entropy measures prediction error for multi-class classification
- Epochs: 10, allowing sufficient iterations for convergence
- Batch Size: 128, balancing computational efficiency and gradient accuracy.

$$Batch\ Update: \theta \leftarrow \theta - \eta \frac{1}{B} \sum_{i=1}^{B} \nabla_{\theta} \mathcal{L}\,(x_i, y_i) \qquad 6$$

Where B=128 is the batch size

- Validation Split: 20% – Portion of data used to evaluate model performance during training.
- Hardware: Google Colab T4 GPU.

2. Callbacks:

- ModelCheckpoint: Saved the model with the lowest validation loss

$$Save\ if\ \mathcal{L}_{val,t} < L_{val,best} \qquad 7$$

- ReduceLROnPlateau: Reduced the learning rate by a factor if validation loss did not improve for a specified number of epochs:

$$\eta \leftarrow \eta\,.factor\ if\ \mathcal{L}_{val,t}\ plateaus \qquad 8$$

- EarlyStopping: Halted training if validation loss did not improve for a set number of epochs, preventing overfitting:

$$Stop\ if\ \mathcal{L}_{val,t} \geq \mathcal{L}_{val,t-p}\ for\ p\ epochs \qquad 9$$

3. Training Behavior:

- Accuracy Improvement: Both training and validation accuracy increased steadily, indicating effective learning
- Convergence: The model stopped improving significantly around epochs 6–8, meaning further training wouldn't help much.
- No Overfitting: The small gap between training and validation accuracy suggests the model generalizes well.

3.4 Process Flow

The illustration in Figure 2 is a step-by-step flowchart of the implementation pipeline for a MLP model designed to perform dynamic bandwidth offloading in a simulated 5G network environment. It clearly maps the process from raw data acquisition to bandwidth allocation decisions.

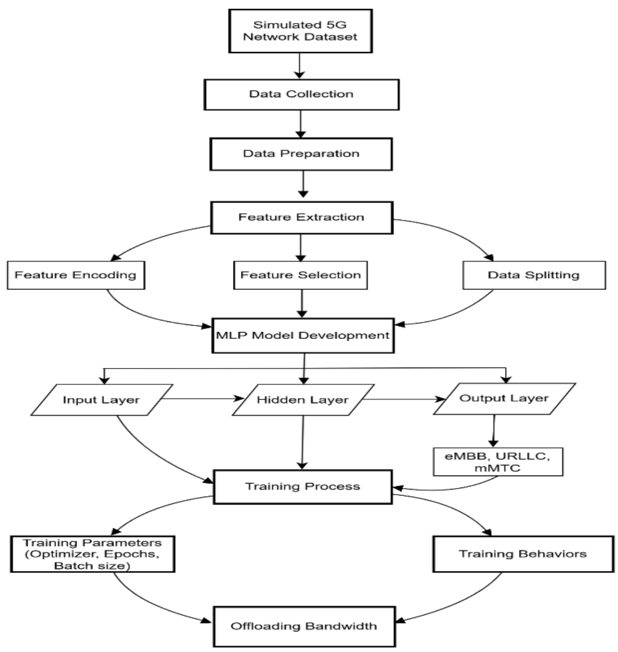

Figure 2: Demonstration Diagram: MLP-Based Offloading

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3.5 Evaluation Metrics

Model performance was assessed using:

- Accuracy: Measures the proportion of correctly classified instances among all predictions.
- Precision: Indicates the percentage of relevant instances among the predicted positive results.
- Recall: Measures the percentage of actual positive cases that were correctly identified.
- F1 Score: Is the harmonic mean of Precision and Recall. It balances both false positives and false negatives.
- Validation Loss: Quantifies the error between predicted and actual outputs on the validation set.

IV. RESULTS

4.1 Performance Evaluation

The MLP model achieved the following performance metrics:

Table 3: Model Evaluation Metrics

Metric	Value
Accuracy	99.82%
Precision	99.56%
Recall	99.78%
F1 Score	99.67%
Loss	0.03238

4.2 Feature Importance

Gain ratio analysis ranked features: Use Case Type (0.54), Packet Loss Rate (0.35), Packet Delay Budget (0.32), Technology Supported (0.29).

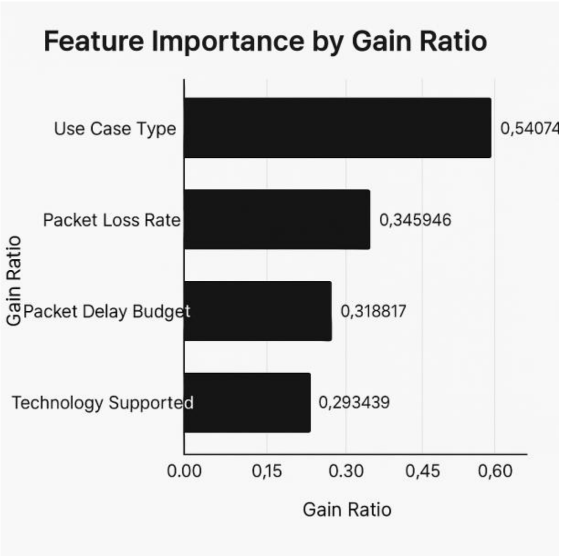

Figure 3: Feature Importance by Gain Ratio

4.3 Confusion Matrix

The model classified all 46,208 samples correctly, showing perfect prediction across all three classes.

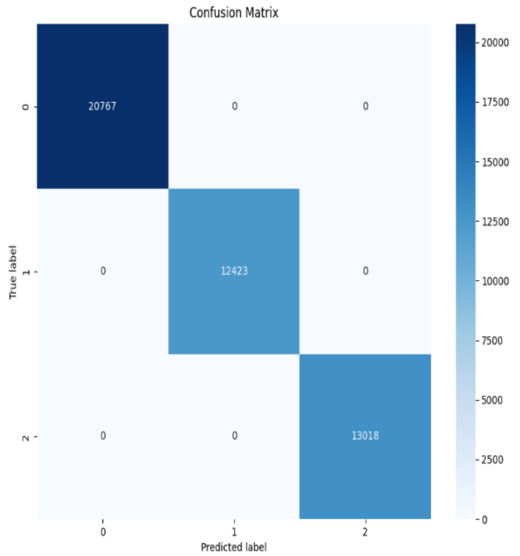

Figure 4: Confusion Matrix of MLP Classifier

4.4 Comparative Analysis

Compared to prior works:

Table 4: Comparative Analysis with Related Works

S/N	Author and Year	Model Used	Dataset Used	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	Menuka et al. (2019)	SVM	SDN Traffic	96.37	-	-	-
2	Thantharate et al. (2019)	DNN	Simulated	93.8	94.1	93.5	93.8
3	Lahoud (2019)	MLP (ADAM)	5G Simulation	97.0	97.2	96.8	97.0
4	Malkoc & Kholidy (2023)	Multiple	Simulated	94.19	93.4	91.52	91.50
5	This Work (2025)	MLP (SGD)	Simulated	99.82	99.56	99.78	99.67

4.5 Learning Curves

The graph illustrates the training process, confirming the model's stability and the effectiveness of overfitting mitigation (e.g., early stopping). The x-axis would range from 0 to 10 epochs, and the y-axes would span 0–100% for accuracy and 0–0.1 for loss. The accuracy curves in Figure 5 rise steeply, stabilizing near 99.82% for both training and validation after epoch 6, indicating convergence.

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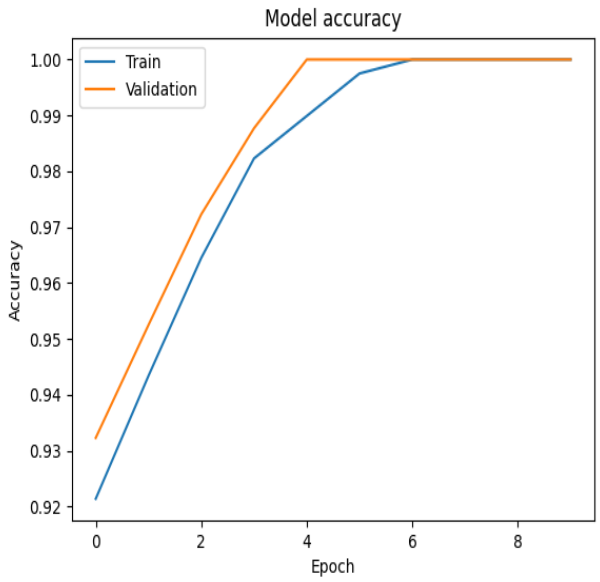

Figure 5: Training and Validation Accuracy Curves

The loss curves in Figure 6 decline sharply, leveling off at 0.03238 for validation, with training loss slightly lower, demonstrating the effect of early stopping (patience=3, min Δloss=0.001).

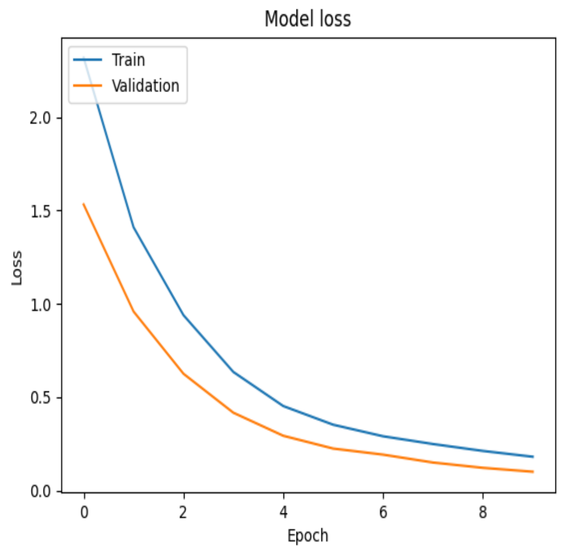

Figure 6: Training and Validation Loss Curves

V. DISCUSSION

5.1 Implications

The deployment of the MLP model in 5G bandwidth allocation reveals strong potential for meeting the diverse QoS demands of heterogeneous services. Specifically, the MLP's capacity to accurately classify service typeseMBB, URLLC, and mMTC demonstrates its adaptability in real-time network scenarios. For instance, in the context of autonomous driving applications that rely heavily on URLLC for ultra-low latency and high reliability, the MLP's precision ensures that these critical data packets are prioritized appropriately, reducing the risk of communication failure. Similarly, in eMBB applications such as high-definition video streaming or immersive virtual reality, the MLP ensures optimal bandwidth allocation, preventing buffer delays and maintaining a high-quality user experience.

The model's layered architecture and use of ReLU and Softmax activation functions contribute to its responsiveness and ability to generalize from input features such as packet delay, loss rate, and use-case type. This allows network operators to implement intelligent, traffic-aware slicing policies that respond dynamically to varying load conditions without manual intervention. Consequently, the MLP offers a scalable and operationally efficient approach for future 5G and potentially 6G deployments.

5.2 Limitations

- The model's inference time is approximately 10 ms per sample, which may pose challenges in high-density or ultra-low-latency environments.
- The training data is based on a simulated dataset of 46,208 samples, which may not fully represent rare or unpredictable real-world 5G traffic patterns.

5.3 Future Work

- Validate the model using real-world 5G network traffic to assess performance under practical conditions.
- Integrate reinforcement learning to enable adaptive, feedback-driven bandwidth allocation.
- Explore hybrid models combining neural networks with heuristic or probabilistic methods to improve efficiency and interpretability, especially for edge deployments.

VI. CONCLUSION

This paper proposed a Multilayer Perceptron (MLP)-based solution for dynamic bandwidth allocation in 5G network slicing, addressing the rigidity and limited adaptability of traditional methods. Through the classification of slice types using key QoS parameters, the MLP model achieved outstanding performance metrics, including 99.82% accuracy, 99.56% precision, and 99.78% recall, with minimal validation loss. These results highlight the model's ability to generalize across diverse service requirements and its suitability for real-time implementation in evolving network environments.

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The architecture's simplicity, coupled with its effectiveness, makes it a promising candidate for intelligent slicing in next-generation networks. However, challenges remain in terms of inference efficiency and real-world applicability. Future research will emphasize validating the model with live traffic data and extending it through reinforcement learning and hybrid techniques, thereby enhancing its scalability, responsiveness, and decision-making autonomy in increasingly complex communication landscapes.

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