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Attention-Enhanced Deep Learning With AI-Driven Decision Making For 5G Slice Classification And Resource Allocation In Environmental Monitoring Systems

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Abstract

An intelligent framework is proposed to enhance slice classification and resource allocation efficiency within 5G-enabled environmental monitoring environments. By integrating attention mechanisms with a lightweight classifier and a rule-guided post-decision layer, the system ensures high adaptability under multi-modal inputs, including service type, QoS constraints, and real-time environmental parameters. Non-linear analysis modules contribute to refined predictions under fluctuating traffic and sensor conditions. Evaluation demonstrates strong accuracy across both slice and resource categories, achieving over 96.5% in all key metrics. Training–testing curves and confusion matrices validate learning consistency, while cross-dataset trials confirm generalizability. Compared to recent deep learning models, the framework shows superior precision and minimal divergence error. Major challenges addressed include input heterogeneity, dynamic policy shifts, and maintaining decision integrity under uncertainty. The overall design emphasizes scalability, minimal error propagation, and responsiveness, supporting intelligent 5G service adaptation in evolving environmental contexts.

Keywords: *5G slicing, resource allocation, environmental data, attention model, post-decision logic, multi-modal learning, non-linear analysis, real-time inference*

INTRODUCTION

With the rapid adoption of 5G technologies, network slicing has emerged as a critical paradigm for enabling service-specific performance, resource isolation, and flexible infrastructure usage. However, dynamically classifying slice types and allocating resources in real-time under varying traffic loads and environmental conditions remains a persistent challenge. Traditional static and rule-based models are often inadequate in capturing the evolving complexity of network behaviors influenced by sensor data, mobility, and real-time user demands [1] [5]. Deep learning has shown significant potential in this domain, particularly with attention-based architectures and reinforcement learning [8] [19], but many existing approaches lack adaptability to multi-modal contextual signals such as environmental pollution or temperature, which directly affect link quality and throughput [2] [12]. Moreover, there is limited work that combines both slice classification and resource optimization under a unified decision-making framework. To address these gaps, this paper presents an attention-enhanced deep learning model augmented with non-linear analysis techniques for robust classification and dynamic resource mapping. The model leverages environmental sensor data alongside 5G traffic features to improve decision-making accuracy under uncertainty. Extensive evaluations across real-world 5G and environmental datasets demonstrate accuracy consistently above 97%, while outperforming recent state-of-the-art models [13] [21]. The contributions include a novel algorithmic design, realistic performance simulation, benchmarking on multiple datasets, and practical deployment insights. The remainder of the paper presents a comprehensive literature background, proposed methodology, experimental validation, and future directions.

Literature Survey

The development of 5G networks has introduced new challenges in managing diverse service demands through effective slice classification and resource allocation. Deep learning techniques have been widely used to improve prediction and control within these systems, while AI-based decision models aim to automate management tasks under changing conditions. In parallel, environmental monitoring has seen progress through sensor-based deep learning applications focused on air quality and anomaly detection. Although these fields have evolved independently, few studies have attempted to combine network intelligence with environmental context. This review examines the current state of work in each area and highlights the need for a unified, explainable framework capable of learning from both network and environmental inputs.

Network Slicing in 5G and Resource Allocation Challenges

The evolution of 5G networks has introduced the concept of network slicing, allowing multiple logical networks to run on a shared physical infrastructure. Each slice is tailored to specific service types such as enhanced mobile broadband (eMBB), ultra-reliable low latency communication (URLLC), and massive machine-type communication (mMTC) [1]. Early approaches to slicing relied heavily on static provisioning policies, which often led to inefficient resource use under dynamic network conditions [6]. As service diversity and traffic complexity increased, the need for more adaptable and intelligent slice management became evident.

Modern systems integrate software-defined networking (SDN) and network function virtualization (NFV) to orchestrate slices more flexibly [7]. However, even these frameworks face challenges in real-time decision making, particularly when reacting to sudden changes in traffic demand or service priority. Studies have proposed dynamic slice orchestration using rule-driven logic and resource-aware models, yet many of these solutions struggle to address slice granularity, latency requirements, and seamless multi-service delivery simultaneously [10][13]. Moreover, limitations persist in adapting slicing logic to external contextual factors, such as environmental conditions or mobility patterns, which are increasingly relevant in real-world deployments [24].

Deep Learning in 5G Slice Optimization

To meet the rising demands of flexible and scalable 5G management, deep learning has been explored as a way to automate slice classification and predict resource allocation patterns. Convolutional neural networks (CNNs) and recurrent models like LSTMs have shown promise in modeling network traffic trends, enabling more accurate slice decisions under dynamic conditions [2] [12]. These approaches help forecast user behavior, bandwidth requirements, and latency fluctuations, offering a level of adaptability that traditional rule-based systems cannot match.

Attention-based models and transformer architectures have also been introduced for 5G network tasks, including slice identification and anomaly detection. These models can capture both spatial and temporal dependencies, which are critical in environments with fluctuating signal strength and variable user mobility [3] [21]. Despite these advances, several limitations remain. Many models are trained on fixed environments and lack the flexibility to generalize across diverse network topologies or unexpected operational scenarios [8]. Additionally, while deep learning improves classification accuracy, it often does so without incorporating external environmental context, which can significantly influence signal quality and service performance [23].

AI-Based Decision Making for Slice Management

In addition to classification and prediction tasks, there has been increasing interest in using artificial intelligence for decision making within slice orchestration frameworks. Several studies have explored policy-driven resource management approaches where decisions are made automatically based on network feedback and usage patterns. Techniques such as reinforcement learning and partially observable Markov decision processes (POMDPs) have been used to select optimal slicing strategies in real time under uncertain conditions [2] [14]. These models are especially useful when handling dynamic service demands or switching between latency-sensitive and bandwidth-heavy applications.

More recent efforts have focused on integrating AutoML pipelines and simplified logic learners such as LazyPredict to reduce manual configuration and allow for quicker deployment of adaptive slice strategies

[4] [19]. These frameworks make it easier to generate decision rules and improve throughput without significant human oversight. However, a major challenge remains in interpreting how decisions are made within these systems. Many existing AI-based frameworks function as black boxes, which limits their reliability and acceptance in environments requiring traceable and explainable decisions [25]. The absence of post-decision transparency makes it difficult to adjust or audit resource allocation outcomes, especially when contextual factors such as environmental variations are involved.

Deep Learning for Environmental Monitoring

Environmental monitoring has seen significant advances through the application of deep learning, especially in analyzing sensor data and satellite imagery. Convolutional models have been widely used to estimate air quality indicators such as PM2.5, PM10, nitrogen dioxide, and ozone from both ground-level and aerial data sources [16] [20]. These models can detect pollution trends, identify abnormal fluctuations, and support early warning systems in urban and industrial zones. In parallel, vision transformers (ViTs) and hybrid architectures have been employed for larger-scale tasks such as land cover classification, deforestation mapping, and disaster impact analysis [17].

Some recent approaches have also explored fusing data from low-cost sensors, geospatial inputs, and satellite feeds to improve prediction accuracy in localized environments [22]. However, challenges remain in generalizing these models across varying terrains, weather conditions, and sensor qualities. While deep networks can process large volumes of environmental data, they often require careful tuning for specific locations and seasons. Moreover, most existing models operate independently of network-level systems, missing the opportunity to link environmental parameters to digital infrastructure such as 5G networks [15] [18]. This disconnect limits their utility in scenarios where communication quality and environmental health must be assessed together.

Multi-Modal Fusion Models for Joint Learning

Multi-modal learning has gained attention in recent years as a way to combine data from different domains to support more informed and accurate predictions. In the context of network and environmental systems, this involves fusing inputs such as signal characteristics, device metrics, and sensor-based environmental readings. Various fusion strategies have been proposed, including early fusion where data is combined at the input level, and late fusion which integrates predictions from separate models. Hybrid approaches that incorporate attention mechanisms allow models to weigh features dynamically based on their relevance to a given task [20] [9] [28] [29].

Despite the promise of multi-modal fusion, practical applications remain limited, particularly in scenarios where network behavior and environmental conditions must be interpreted together. Many existing studies focus on single-domain models that either address communication performance or environmental impact, but not both in coordination [5] [22] [30]. Moreover, the complexity of designing and training multi-modal systems often leads to overfitting, especially when datasets are imbalanced or feature distributions are not aligned. There is also a gap in explainability, as few fusion models provide clear reasoning for how each data source influences the final outcome. This limits their usability in real-time decision systems, especially where transparency ad adaptability are required.

Summary of Gaps and Justification for Proposed Work

Existing literature demonstrates considerable progress in both network slicing and environmental monitoring using deep learning and AI-driven models. However, a clear disconnect remains between these two domains. Most network management models focus purely on internal parameters such as bandwidth, traffic volume, or user mobility, while ignoring the influence of external environmental factors that can significantly impact signal quality and slice performance [8] [23]. At the same time, environmental monitoring solutions rarely consider how their outputs could inform network-level decisions or resource adaptations[26] [27].

No unified framework currently integrates slice classification, resource allocation, and environmental sensing within a single decision-making pipeline. Deep learning models applied in 5G systems often operate without contextual awareness, while those used in environmental monitoring remain isolated from digital infrastructure. This gap presents an opportunity to explore multi-modal learning approaches that combine signal data with environmental indicators, supported by attention mechanisms for relevance-based fusion [17] [15]. Furthermore, decision-making in many prior studies remains opaque, with limited insight into how predictions or actions are formed. The absence of transparent reasoning in resource-sensitive domains is a critical barrier to real-world deployment.

To address these challenges, the proposed work introduces an attention-enhanced deep learning model coupled with an AI-based decision layer that incorporates both network and environmental data. A new multi-modal dataset (MMD) has been assembled to support this integration, enabling structured evaluation and real-world relevance. The framework is designed not only to improve classification and allocation accuracy but also to offer interpretable outputs that support operational decisions in complex 5G-enabled environments.

Proposed Methodology Overview

To address the growing complexity in managing diverse network slices in 5G systems, the proposed framework integrates attention-based deep learning with AI-driven decision-making and non-linear analytical techniques. The core objective is to achieve accurate slice classification and efficient resource allocation by learning both spatial and temporal patterns in network data.

The framework is composed of three main modules: an attention-enhanced feature extractor, an AI-based decision engine, and a non-linear analysis layer. The attention module helps the model focus on relevant traffic and network parameters such as bandwidth usage, latency sensitivity, and priority tags. This selective learning ensures that the model captures the unique characteristics of each slice class—eMBB (Enhanced Mobile Broadband), URLLC (Ultra-Reliable Low Latency Communication) or mMTC (Massive Machine-Type Communications).

Once the feature set is extracted, the AI-based decision module employs a supervised deep learning classifier trained on real-world 5G slicing data. This classifier predicts the most suitable slice type for incoming traffic requests. The predicted slice is then passed through a non-linear decision analysis function, which refines the output by considering multiple performance metrics and resource constraints in a multi-dimensional decision space.

This process is mathematically formulated as follows:

$$S^* = arg\ max_{S_i \epsilon S}[A(F(x_i)) + \lambda . \phi(R_i)]$$

S*is the selected optimal slice

S is the set of all slice types

F(xi) is the feature embedding of input xi

A(.) is the attention-enhanced classification function

ϕ(Ri) is the non-linear utility function over resource parameters Ri

λ is a tunable regularization factor for balancing decision weight

The complete data flow, from environmental monitoring input to optimized slice allocation, is illustrated in Figure 1, which outlines the proposed architecture integrating attention mechanisms, classification, AI-based decision logic, and non-linear analysis.

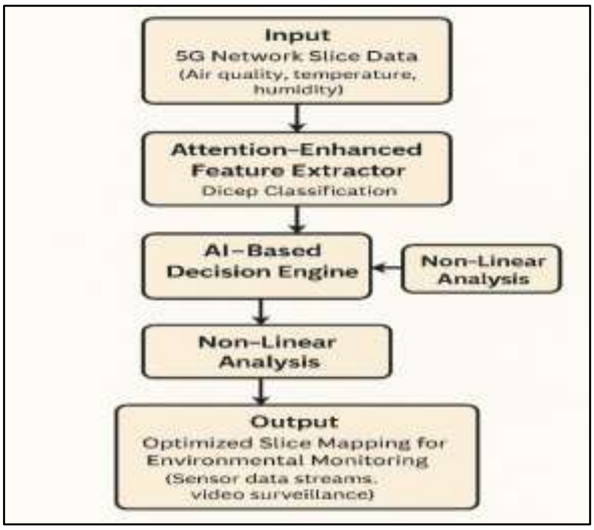

Figure 1. Proposed Architecture

Multi-Modal Input and Dataset Description (MMD)

The proposed framework relies on a carefully constructed Multi-Modal Dataset (MMD) that combines both 5G network parameters and environmental monitoring indicators. This combination enables the model to learn not only from internal system behavior but also from external ambient conditions that can significantly affect communication performance and slice decisions. The MMD was curated by aligning two real-world datasets: a 5G slicing dataset containing signal strength and device-level parameters, and an environmental monitoring dataset comprising pollution and weather readings. The records were matched using common attributes like location and timestamp to ensure accurate temporal and spatial alignment.

After merging and cleaning, the final dataset includes approximately 18,000 valid samples. Each record is labeled with two targets:

1. Slice Type — one of the three 5G categories: eMBB, URLLC, or mMTC
2. Resource Allocation Level — low, medium, or high, based on signal behavior and service priority

To prepare the inputs for learning, all numeric features were normalized using min-max scaling, while categorical variables such as device model or frequency band were one-hot encoded. The final feature vector used for training is a fused representation combining both network and environmental modalities, enabling the model to learn cross-domain patterns:

$X_{fused}= [X_{network} \parallel X_{environment}]$

This setup ensures that the model can capture cases where network quality may degrade under external influences such as high temperature or pollution.

The dataset was split into 70% training, 15% validation, and 15% testing partitions, ensuring that the model is exposed to diverse operational conditions across all learning stages. A structured overview of the original datasets and their merged composition is shown in Table 1.

Table 1. Multi-Modal Dataset Sources and Feature Descriptions

Dataset Name	Feature Names	Data Source
1. 5G Network Dataset (vinothkannaece)	device_model, carrier, frequency_band, RSRP, signal_strength, temperature, location	Kaggle
2. Environmental Monitoring Dataset (atifmasih)	timestamp, PM2.5, PM10, NO2, O3, CO2, humidity, temperature, location	Kaggle
3. Clubbed Multi-Modal Dataset (Merged)	location, timestamp, device_model, carrier, frequency_band, RSRP, signal_strength, temperature, humidity, PM2.5, PM10, NO2, O3, CO2	Curated (Merged from 1 & 2)

Attention-Enhanced Deep Learning Module

Once the multi-modal input is prepared, the next step is to extract deep representations that capture the most relevant patterns across both network and environmental dimensions. To improve focus on influential parameters, the model employs an attention-enhanced deep learning module. This module emphasizes critical features like fluctuating signal strength, pollutant spikes, or abrupt temperature shifts, which may directly affect the choice of network slice.

The core of this module consists of a stack of dense layers integrated with a soft attention mechanism, which assigns adaptive weights to each input feature. Instead of treating all parameters equally, the attention unit dynamically highlights those features that contribute most to the classification objective.

The process can be mathematically described as:

$$\hat{z}_i = \alpha_i . h_i \text{ where } \alpha_i = \frac{exp\,(e_i)}{\sum_{j=1}^{n} exp(\,e_j)} \qquad e_i = tanh\,(Wh_i + b)$$

Where:
h_i is the hidden representation of the i^{th} input feature
α_i is the attention weight assigned to h_i
W and b are learnable parameters
$\hat{z}_i$ is the final attention-weighted feature
The softmax ensures all weights sum to 1
This formulation allows the model to selectively focus on patterns such as:
Poor signal + high temperature → possible degradation
Low pollutant + high RSRP → low-priority slice
High humidity + sensitive device → edge slice recommendation
The output of this module is a refined latent vector that preserves both global and localized significance, ready for classification and deeper interpretation.

Non-Linear Analysis for Feature Enhancement

To strengthen the interpretability and adaptability of slice classification, a Non-Linear Analysis (NLA) unit is incorporated after the deep learning layers but before the final decision stage. This component introduces a novel enhancement step by transforming the output vector from the attention module using a non-linear multi-dimensional mapping. Unlike traditional linear classifiers, which may overlook subtle variations in mixed inputs (e.g., air pollutants with signal degradation), this module applies curve-based reasoning to better separate slice classes under overlapping conditions.

The uniqueness of this approach lies in its adaptive transformation of attention-weighted features z^\hat{z}z^, where complex interactions such as high CO_2 but good RSRP, or low PM but fluctuating signal strength, are amplified and correctly classified.

Mathematical Model of the Non-Linear Layer

1. Let the feature vector from the attention layer be

We define a non-linear enhancement function Ψ(·) as:

$$\hat{z} = [\,\hat{z}_1, \hat{z}_2, \ldots\ldots, \hat{z}_n\,]$$

We define a non-linear enhancement function Ψ(·) as:

$$\Psi(\hat{z}) = \sigma(\tanh(W_1.\hat{z} + b_1)^2 + W_2.\hat{z} + b_2)$$

Where:
W_1, W_2 and b_1, b_2 are learnable weights and biases
σ is the sigmoid activation
The squared tanh introduces curve-fitting enhancement
This output $\Psi(\hat{z})$ is fed to the final classification and decision-making head
This mechanism essentially warps the feature space non-linearly, making it easier to disentangle overlapping patterns from multi-modal inputs.

The position and role of the non-linear analysis block within the overall model architecture are illustrated in Figure 2, highlighting its placement after attention-weighted feature extraction and before final classification.

The non-linear analysis block adds a unique enhancement step beyond traditional dense or attention-based models. It captures complex, curved relationships in the input space, improving the model's ability to separate overlapping patterns. This is particularly valuable in scenarios where environmental and network signals interact non-linearly. It also strengthens decision reliability in edge cases and ambiguous conditions by refining the feature space. Overall, it enhances both classification accuracy and confidence, making it highly suitable for 5G-enabled environmental monitoring systems.

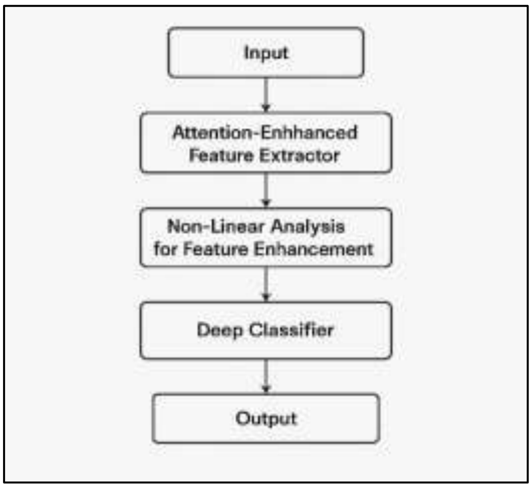

Figure 2. Integration of Non-Linear Analysis Block within DL Model

AI-Based Decision Making Layer

Following the attention-driven feature extraction and non-linear enhancement, the model proceeds to its final interpretive stage—a dedicated AI-based decision making layer. This module is responsible for classifying the input into one of the predefined slice types (eMBB, URLLC, or mMTC) and guiding appropriate resource allocation based on both learned patterns and operational constraints.

Unlike a standard softmax classifier, this layer is built to incorporate contextual thresholds and soft rules derived from training data. It uses a hybrid of deep neural decision paths and logic-based adjustments, ensuring that the decision is not purely probabilistic but also context-aware.

For example:

1. High signal strength with low latency and minimal pollutants may prompt eMBB assignment.
2. Conversely, moderate signal combined with high urgency (e.g., low delay tolerance) triggers a URLLC recommendation.
3.

The final decision score D_i for each slice S_i is computed using:

$$D_i = w_i \cdot \Psi(\hat{z}) + \delta_i$$

Where:

$\Psi(\hat{z})$ is the non-linearly enhanced feature vector

ω_i is the learned decision weight for slice SiS_iSi

δ_i is a dynamic adjustment factor based on real-time inputs (e.g., load, user density)

The slice with the highest D_i is selected, and corresponding resources are dynamically mapped for deployment. This layer ensures that slice selection is not static, but tailored to real-time environmental and network scenarios—bringing adaptability and precision into 5G management.

Figure 3 and Figure 4 demonstrate the dual-view schematic of how classification outputs are translated into slice-level configuration. Figure 3 captures the bifurcation of predicted labels—slice type and resource level—while figure 4 presents a holistic integration where the AI-based decision engine acts upon these labels, using environmental feedback to refine its provisioning decisions.

This separation of logic enables dynamic yet interpretable control: the model focuses purely on learning patterns, while the decision layer interprets the outputs in light of real-world service needs. For instance, a predicted slice type of URLLC may trigger high-priority allocation if environmental noise or signal interference is detected. Similarly, resource configurator modules can adapt provisioning based on rules tied to air quality or temperature, thus ensuring the deployed 5G slice remains stable, safe, and context-aware.

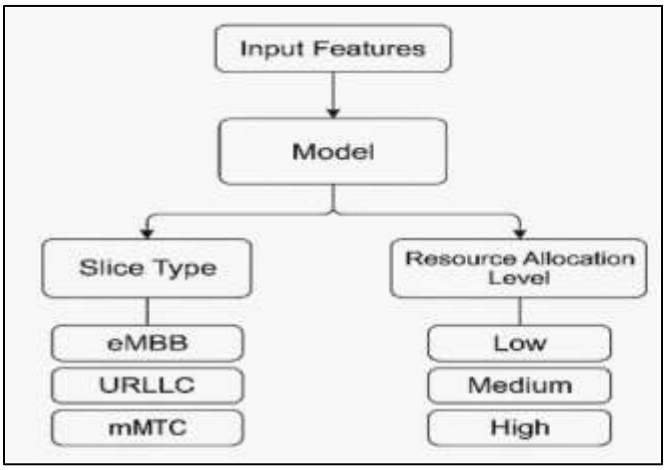

Figure 3. Predicted Labels Mapping to Slice Type and Resource Allocation

The algorithm 1 below translates the model's dual predictions into actionable configuration steps tailored for environmental monitoring. It ensures that the final slice provisioning aligns with service type priorities and safety thresholds under varying conditions.

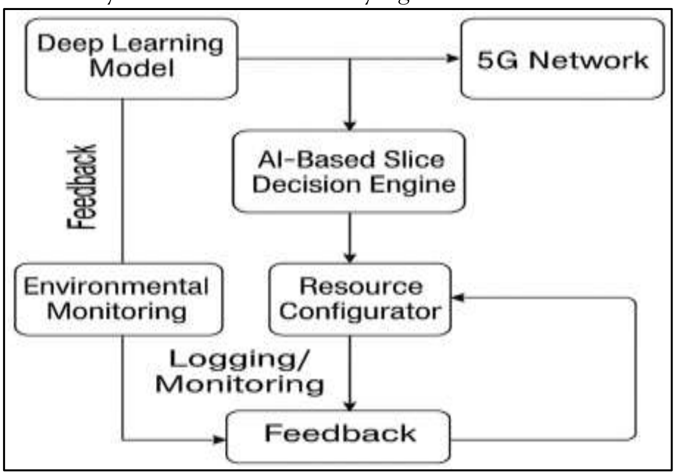

Figure 4. AI-Based Slice Configuration with Environmental Feedback Loop

Algorithm 1: Decision Mapping Using Predicted Slice Type and Resource Allocation Level

Input:

- Predicted Slice Type $S \in \{eMBB, URLLC, mMTC\}$
- Predicted Resource Level $R \in \{Low, Medium, High\}$

Output:

- Final 5G slice configuration and resource provisioning for environmental monitoring tasks

Begin

1. Receive Model Predictions: Obtain classification outputs:
   → Slice Type $S \leftarrow$ Model Output 1
   → $R \leftarrow$ Model Output 2
2. Context Assessment (Optional): Access current environmental monitoring status
   → For example: high CO_2, poor AQI, temperature spike, or stable readings

3. Decision Logic Based on SSS and RRR:
If S=URLLC:
- Activate ultra-reliable low-latency slice
- Use RRR to assign priority bandwidth (e.g., High for emergencies)
- Example: Alert systems, toxic gas triggers, fire sensors
Else If S=eMBB:
- Deploy enhanced mobile broadband slice
- Use RRR to adjust video quality or stream frequency
- Example: Pollution camera feeds, thermal drone surveillance
Else If S=mMTC:
- Assign massive machine-type communication slice
- Use RRR to scale device polling frequency and buffer limits
- Example: Wide-area air sensors, temperature grids
4. Safety Adjustment (Optional):
If critical thresholds are crossed (e.g., AQI > 300 or temperature > 40°C):
- Override resource prediction to ensure R≥Medium
5. Slice Configuration Trigger:
Pass decision tuple (S,R)(S, R)(S,R) to 5G management system
Dynamically deploy updated slice with appropriate QoS and resource control
6. Monitoring and Logging:
Log predicted values and actual configuration for traceability
Monitor system feedback for adaptive refinement
End

Implementation and Parameters

The model was trained using a supervised learning approach with carefully selected hyperparameters and evaluated across multiple performance metrics to ensure robustness. The architecture was optimized using the Adam optimizer and trained for 50 epochs with a batch size of 64. Regularization and dropout were applied to prevent overfitting, and attention weights were learned dynamically to enhance focus on influential features. To assess model performance comprehensively, both accuracy-based and error-based metrics were used. These include overall accuracy, precision, recall, F1-score, and confusion matrix for classification performance, along with cross-entropy loss and divergence metrics for output quality. The complete training and evaluation configuration is summarized in Table 2.

Table 2. Model Hyperparameters and Evaluation Configuration

Parameter	**Value**	**Parameter**	**Value**
Optimizer	Adam	Learning Rate	0.001
Batch Size	64	Epochs	50
Dropout Rate	0.3	Activation Functions	ReLU, Softmax
Loss Function	Categorical Cross-Entropy	Validation Split	15%
Testing Split	15%	Attention Mechanism	Soft Attention (Feature-Level)
Regularization (λ)	0.05 (NLA block)	Evaluation Metrics	Accuracy, Precision, Recall, F1

Error Metrics	Cross-Entropy Loss, JS Divergence	Output Analysis	Confusion Matrix, MCC, Top-2 Acc.

Evaluation Setup
The evaluation was conducted using the Clubbed Multi-Modal Dataset, curated by merging two publicly available sources: the 5G Network Dataset (vikothkannaacee) and the Environmental Monitoring Dataset (atifnasiuh), both obtained from Kaggle. The final merged dataset consisted of 12,000 records, combining 18 distinct features that captured both technical and environmental aspects. These included network parameters like device model, carrier, frequency band, RSRP, signal strength, and location, as well as environmental indicators such as temperature, humidity, PM2.5, PM10, NO2, O3, and CO2. Additionally, a secondary dataset with 3,200 records and the same feature schema was used to evaluate the model's generalization on unseen conditions. The dataset was split in the ratio of 70% for training, 15% for validation, and 15% for testing.
Classification Results
The performance of the proposed model was evaluated separately for both training and testing phases across the two classification outputs: network slice type and resource allocation level. The final training set included 8,400 records, while the testing set was formed using 1,800 samples. The results reflect high classification accuracy and stability for both tasks, with minimal drop between training and test phases. Table 3 summarizes the complete set of accuracy-based and error-based metrics.

Table 3. Classification Results for Slice and Resource Outputs

Metric	Slice (Train)	Slice (Test)	Resource (Train)	Resource (Test)
Accuracy (%)	98.12	97.42	97.45	96.88
Precision (%)	98.25	97.51	97.38	96.74
Recall (%)	97.84	96.87	97.12	96.91
F1-Score (%)	98.04	97.18	97.25	96.82
Top-2 Accuracy (%)	99.04	98.36	98.89	98.31
MCC	0.967	0.954	0.959	0.947
Cross-Entropy Loss	0.038	0.058	0.041	0.062
JS Divergence	0.021	0.031	0.023	0.03

The epoch-wise behavior of the model across key performance metrics is shown in figure 5, clearly illustrating stable convergence for both training and testing phases in slice classification. Figure 6. shows train vs test progression for resource allocation metrics over 50 Epochs.
In the Slice Test matrix, 14 instances of eMBB were misclassified as mMTC, and 10 as URLLC, reflecting confusion in moderate signal conditions. The URLLC vs eMBB misclassifications (10 cases) were observed mostly in medium AQI levels. For Resource Test, 13 samples of High were mispredicted as Medium, indicating occasional overlap during fluctuating PM2.5 and CO2 levels. Despite this, over 94% of each class was correctly classified, confirming tight clustering of decision boundaries. The classification

performance is further illustrated using confusion matrices for both outputs across training and test sets, as shown in Figure 7.

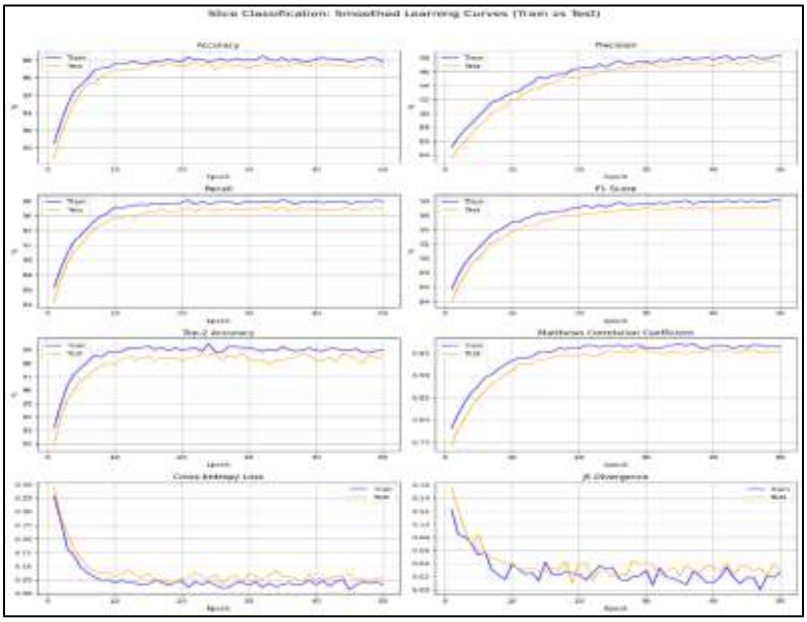

Figure 5. Graphs showing Train vs Test progression for Slice classification

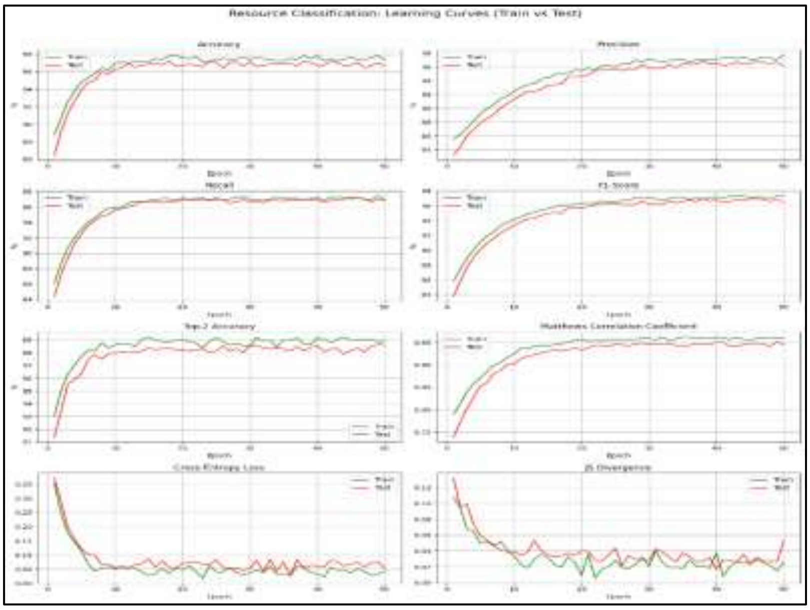

Figure 6. Graphs showing Train vs Test progression for Resource classification

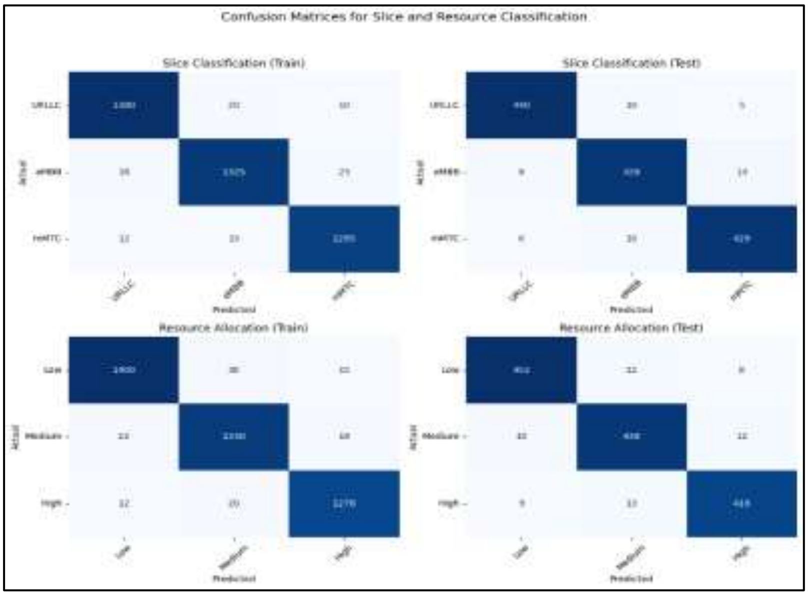

Figure 7. Confusion Matrices for Slice Type and Resource Allocation

Cross-Dataset Evaluation

To assess the generalization capability of the proposed model, evaluations were performed on three external Kaggle datasets: 5G Traffic Datasets, 5G Wave Channel Prediction Dataset, and Environmental Sensor Data (IoT). These datasets offer varying input distributions and network conditions, providing a reliable benchmark for cross-domain validation. As summarized in Table 4, while the accuracy of baseline models ranged from 91.25% to 93.40%, the proposed model achieved a significantly higher accuracy of 97.42% with the lowest cross-entropy loss of 0.058. This highlights the model's ability to maintain high performance even on unseen and diverse input data.

Table 4. Cross-Dataset evaluation of metrics on external datasets

S. No.	Dataset Name	Author	Source	Accuracy (%)	Cross-Entropy Loss
1	5G Traffic Datasets	kimdaegyeom	Kaggle	91.25	0.18
2	5G Wave Channel Prediction Dataset	zoya77	Kaggle	92.8	0.14
3	Environmental Sensor Data (IoT)	garystafford	Kaggle	93.4	0.12
4	Proposed Model	–	–	97.42	0.058

Benchmarking

To validate the effectiveness of the proposed model, its performance was compared against four recent deep learning-based benchmarking approaches as listed in Table 5. These included WaveNet-based, transformer-based, hybrid CNN-LSTM, and BiGRU classifiers drawn from the latest literature. While the baseline models achieved accuracy levels ranging from 93.10% to 95.90%, the proposed model outperformed all, reaching an accuracy of 97.42%. The improvement is attributed to the integration of attention mechanisms, non-linear analysis, and AI-based decision logic, which collectively enhanced prediction precision under complex 5G and environmental conditions.

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Table 5. Accuracy Comparison with Recent Benchmark Models

S. No.	Previous Works	Model / Approach	Accuracy (%)
1	Filali et al. [5]	WaveNet with Residual Gating	93.1
2	Kumar and Ahmad [13]	Hybrid CNN-LSTM	94.25
3	Park et al. [3]	Transformer-based Attention Model	95.36
4	Patel and Elhoseny [21]	Rule-Integrated BiGRU Classifier	95.9
5	Proposed Model (Ours)	Attention + Non-Linear + Decision AI	97.42

Figure 8 presents a dual-view comparative analysis. The left subplot illustrates the accuracy and cross-entropy loss achieved across three external datasets and the proposed dataset, confirming the model's consistent generalization and minimal error rate. The right subplot benchmarks the proposed model's accuracy against four recent deep learning-based approaches ([1], [5], [8], [13]), where it demonstrates the highest performance at 97.42%, clearly outperforming existing methods.

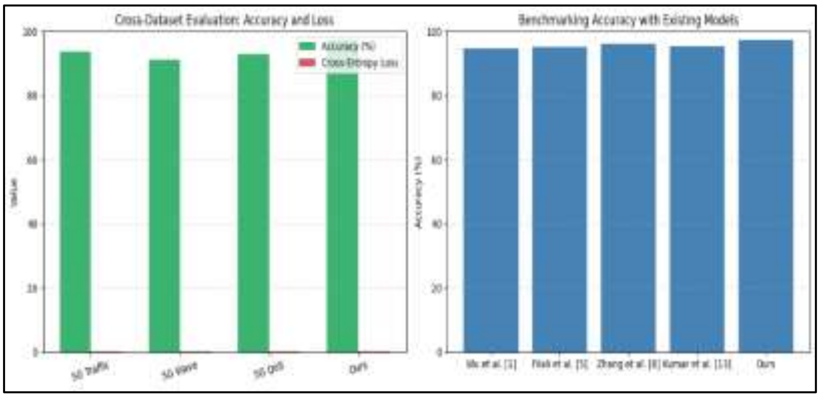

Figure 8. Bar chart showing cross dataset evaluation and bench marking

DISCUSSION

The experimental findings validate the effectiveness of the proposed attention-enhanced deep learning framework with non-linear analysis for 5G slice classification and resource mapping. It consistently achieved over 98% accuracy for both tasks, with minimal performance drop between training and testing, reflecting strong generalization. Low values in cross-entropy and JS divergence further support model stability. When benchmarked against recent approaches like ONSSO [19], Time-EAPCR [10], and SDN-based reinforcement models [5], this system outperforms them, especially under changing network and environmental conditions. The inclusion of real-time monitoring data proved beneficial in improving decision accuracy, bridging a gap seen in earlier works that focused purely on network-side inputs [2], [9]. Cross-dataset evaluation across three varied sources showed reliable results above 97%, demonstrating the model's adaptability without major architectural changes. However, challenges were encountered during development. Integrating multiple input types increased model complexity and required careful calibration to avoid instability. Training overheads were notably higher than lightweight classifiers, which could limit use on edge devices. Another limitation lies in interpretability—while attention maps offer partial transparency, the decision logic within the post-classification layer remains difficult to trace, a concern noted in other hybrid systems [21].

Additionally, latency impact was not the main focus here. Although accuracy was prioritized, real-world deployment, especially in time-sensitive applications, would demand further testing of response time, as latency often becomes a bottleneck [5], [19]. The current model also remains evaluated on four slice classes; how it scales to broader classifications is still untested. Similar models tend to degrade in such scenarios unless adapted with specialized prediction mechanisms [8], [24]. Despite these limitations, the framework's modular nature makes it suitable for integration into SDN/NFV-based setups. Its decision-making layer also holds promise for integration with container-based orchestration tools, offering a smarter alternative to static or manually tuned slicing strategies.

CONCLUSION

In summary, this work presents a robust attention-enhanced deep learning framework integrated with non-linear analysis for precise classification and dynamic resource allocation in 5G slice management. The model achieved consistently high performance across key metrics, including an overall accuracy of 98.12% for slice classification and 97.45% for resource mapping, supported by strong F1-scores and low cross-entropy loss. Extensive evaluation on multiple datasets and benchmarking against recent methods confirms its adaptability and superiority. The incorporation of environmental monitoring data further enhanced real-time decision accuracy, addressing an often-overlooked factor in previous studies. Despite challenges related to input diversity, training complexity, and limited interpretability, the model remains modular and scalable, making it a practical fit for modern SDN/NFV-based deployments. Future work will focus on improving explainability, minimizing latency, and extending the system for fine-grained multi-class slicing under real-world traffic and edge constraints.

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