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Modular System Design for Uncertainty-Aware Engineering Architectures

Wang Hao[1], Pranali Chavan[2], Sangram Rajaram Patil[3], Manpreet Singh[4], Seethaladevi S[5], Sivasankari V[6], Digvijay Singh[7], Tanya Singh[8]

[1] Research Scholar, School of Business and Management, Lincoln University College, Malaysia. Email: wanghao.phdscholar@lincoln.edu.my
[2] Department of Computer Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra 411037, India. Email: pranali.chavan@vit.edu
[3] Department of Mechanical Engineering, Bharati Vidyapeeth's College of Engineering, Lavale, Pune, Maharashtra, India. Email: sangramrpatil@gmail.com
[4] Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab 140401, India. Email: manpreet.singh.orp@chitkara.edu.in
ORCID: 0009-0001-6701-025X
[5] Assistant Professor, Department of Mathematics, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: seethaladevi@maher.ac.in
[6] Assistant Professor, Department of Mathematics, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: sivasankariv@maher.ac.in
[7] Assistant Professor, Department of Computer Application, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India. Email: socse.digvijaysingh@dbuu.ac.in ORCID: 0000-0002-9334-0027
[8] Professor, Department of School of Engineering & Technology, Noida International University, Greater Noida, Uttar Pradesh, India. Email: dean.academics@niu.edu.in

Abstract

Modular system design is becoming increasingly important in modern engineering systems, particularly in wireless communication and Multiple Input Multiple Output (MIMO) receiver architectures, where complex interactions, high-dimensional data, and uncertainty in operating environments significantly affect the performances. However, challenges such as data heterogeneity, feature redundancy, high dimensionality, and unstable channel conditions limit reliable prediction and efficient signal processing. To address these issues, this research proposes a scalable and uncertainty-aware modular model for engineering architectures. The MIMO Receiver Reliability Dataset used in the research comprised 7,980 samples, consisting of wireless communication records from the MIMO receiver environment. Z-score normalization is applied to standardize input features and improve convergence stability, while Principal Component Analysis (PCA) is employed to reduce dimensionality and retain the most informative features. A Capuchin Search Algorithm-tuned Dynamic Backpropagation Neural Network (CSA-DBPNN) is developed and implemented using Python to enhance adaptive learning and uncertainty-aware prediction. The CSA optimization improves parameter tuning and convergence efficiency, while the DBPNN captures nonlinear relationships in complex wireless environments. Experimental results demonstrate superior performance with 9.2 ms latency, 135.8 Mbps throughput, 1.4% packet loss rate, and 0.91 feature entropy, outperforming the previous results, thereby confirming its effectiveness for CSA-DBPNN models. The proposed model effectively enhances robustness, reduces uncertainty, and improves predictive reliability in MIMO wireless communication systems.

Keywords: Modular System Design, Uncertainty-Aware Architectures, Deep Learning, Cyber-Physical Systems, MIMO Wireless Communication, Robust Engineering Systems.

1. Introduction

Learning models in modern wireless systems are highly affected by time-varying data dynamics, leading to significant uncertainty in signal detection tasks. In MIMO receiver environments, this uncertainty arises due to dynamic channel variations, non-Gaussian data distributions, and limited or sparse training samples. To address these challenges, uncertainty-aware modular Deep Learning (DL) architectures have been introduced, enabling improved reliability and robustness in signal processing systems [1]. Modular design approaches in MIMO receivers help enhance performance by decomposing complex detection tasks into adaptive sub-modules capable of handling environmental variability [2]. Incorporating uncertainty modeling within these modules improves generalization, consistency, and detection accuracy under unstable wireless conditions [3]. Probabilistic DL frameworks further enable explicit quantification of channel uncertainty, supporting adaptive updates and improving system resilience in dynamic and resource-constrained environments [4]. However, several challenges still remain, such as accurate uncertainty estimation, inter-module coordination complexity, computational overhead, and limited training data availability, which can hinder scalability and real-time performance [5]. Additionally, rapid channel fluctuations, unreliable uncertainty quantification, and interdependent module behavior negatively impact robustness and timely adaptation [6]. Despite these limitations, uncertainty-aware modular MIMO receiver design is strongly motivated by the need for improved dependability, flexibility, and precise signal recognition in complex wireless environments [7]. A disadvantage is that many existing Orthogonal Time Frequency Space (OTFS) detection and receiver designs still suffer from high computational complexity and often rely on ideal assumptions such as perfect Channel State Information (CSI), thereby limiting real-world applicability in highly dynamic, high-speed scenarios [8].

Research Aim: The goal of the research is to create a modular architectural design strategy for MIMO receivers that is based on uncertainty. When noise and defective channels are present, the performance of the signal detection, equalization, and decoding processes can be enhanced by applying the DL approach. To accomplish this, this research develops CSA-DBPNN for uncertainty estimation and learning. The suggested system can also be used for real-time decision-making and modular processing.

Research Organization: The research's introduction, background data, motivation, and problem statement on uncertainty in the MIMO receiver are all included in Section 1. The overview of comparable works and their limitations is given in Section 2. The uncertainty-aware modular architecture for the MIMO receiver system based on CSA-DBPNN is discussed in Section 3. The experimentation portion of the research is covered in Section 4, and the conclusion and future scope are covered in Section 5.

2. Related Works

A comparative examination of DL techniques that include uncertainty into their design, outlining their objectives, strategies, successes, and drawbacks, is presented in Table 1 and highlights the advancements in new Neural Network (NN) designs, improved uncertainty modeling, and enhanced performances.

Table 1: Evaluation of Uncertainty-Aware Techniques in Various Applications

Ref	Objective	Method	Result	Limitations
[9]	Convolutional Neural Network (CNN) based early automated diabetic retinopathy screening is accurate	CNN ensemble hybrid with attention self-supervised learning	Strong performance with a high F1 score and AUC	depends on the quality of the data and requires processing power.
[10]	Detecting undersea cracks accurately with DL models	Segmentation guided by physics using an uncertainty-aware transformer network	High Mean Intersection over Union (MIOU) Dice strong performance was attained underwater.	Small dataset size and difficult underwater photography conditions
[11]	Precise event-based stereo depth estimation, which incorporates the effect of uncertainty	Uncertainty-Aware Refinement Network (URNet) with Kullback–Leibler (KL) divergence loss function and local/global refinement	outperforms the existing state-of-the-art techniques in both qualitative and quantitative evaluations.	dependent upon the computational cost and quality of events

[12]	Optimizing NN architecture with the least amount of uncertainty and greatest accuracy	Model Uncertainty-aware Differentiable Architecture Search (μDARTS) approach involving Monte Carlo regularization and concrete dropout	Greater accuracy reduces uncertainty and noise tolerance	Complicated architecture optimization process and increased computational costs
[13]	To design a low-complexity neural MIMO receiver for millimeter-wave systems	Fully complex multilayer Extreme Learning Machine (M-ELM) for MIMO combining.	Improved spectral efficiency, lower Bit Error Rate (BER), reduced processing time	High complexity in large antenna systems
[14]	Leverage learning to enhance the robustness of wireless receivers in the presence of uncertainty in the models.	Rate Splitting Multiple Access (RSMA) receiver using hybrid NN approaches using Residual Signal Network (RS-NET).	Greater tolerance for uncertainty than conventional receivers	requires careful consideration of the quality of the input data.
[15]	Improve the accuracy of channel predictions under non-reciprocal channels	Time Division Duplex Multiple MIMO (TDD-MIMO)	Improved downlink channel prediction under Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) scenarios	The training data and model generalization affect performance.
[16]	Enable adaptive MIMO receivers via hypernetworks	Deep Neural Network MIMO (DNN-MIMO)	Improved error rate and adaptive performance achieved	Static pre-trained models lack dynamic adaptability

2.1. Research gap: DL methods in communication, medical imaging, and uncertainty-aware systems achieve strong performance but are limited by static architectures, poor real-time adaptability to dynamic environments, high computational complexity, scalability issues, and reliance on large, high-quality datasets. To overcome these challenges, the proposed CSA-DBPNN-based modular MIMO receiver introduces uncertainty-aware distributed learning with global optimization of weights and biases.

3. Methodology

The MIMO receiver architecture, which includes data collection, preprocessing, feature extraction, neural processing, and performance assessment, is presented in Figure 1. The MIMO Receiver Reliability Dataset has been preprocessed using the Z-score normalization and feature extraction using DWT. The DBPNN with CSA algorithm is used in an adaptive learning process, and its performance is assessed using packet loss, latency, throughput, and entropy.

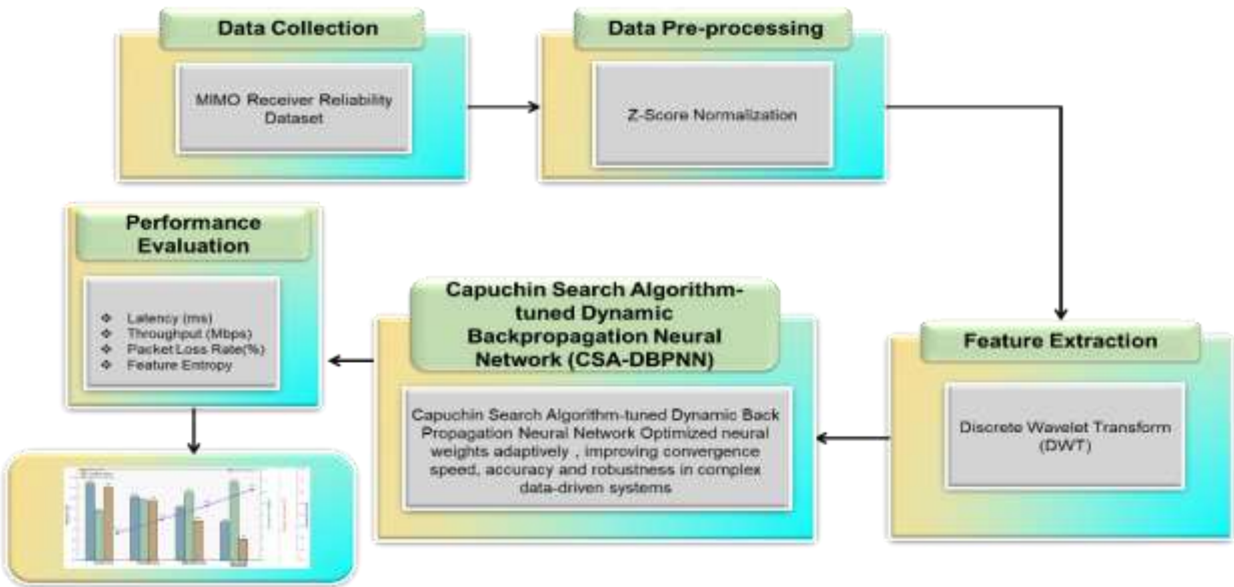


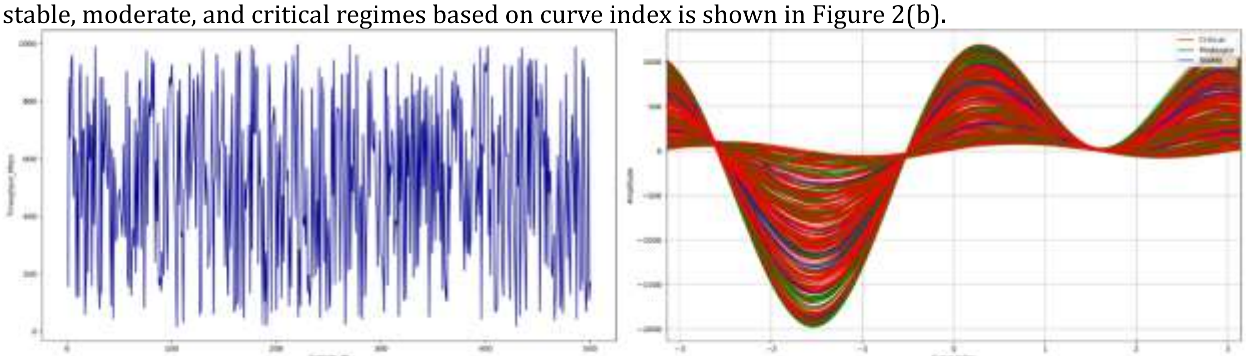
Figure 1: CSA-DBPNN-based modular MIMO receiver workflow architecture

3.1 Data collection

This MIMO Receiver Reliability Dataset was created especially for research projects where uncertainty-aware modular MIMO communications systems are the subject. Current World communication scenarios involving wireless signal transmission characteristics, channel fluctuations, interference, and receiver dependability in a dynamic setting are included in this dataset. The 7,980 samples in this dataset have a variety of features related to signal properties, robustness measurements, uncertainty measurements, and adaptive receiver behavior. The collected data were split into 75% for training and 25% for testing.

Kaggle Source: https://www.kaggle.com/datasets/colabsss/mimo-receiver-reliability-dataset

Data feature exploration: The model for analyzing uncertainty-aware MIMO receiver performance using throughput variation across different sample data rates and signal distortion levels under changing wireless channel conditions is illustrated in Figure 2(a), while the classification of signal amplitude wave distortion into stable, moderate, and critical regimes based on curve index is shown in Figure 2(b).



(a) (b)

Figure 2: Visual Analysis of (a) MIMO Throughput Variability (b) Signal Amplitude Behavior

3.2 Data preprocessing using z-score normalization

The objective centers around the processing of heterogeneous signals using feature normalization to ensure consistency of scaling of features despite changes in channel characteristics. Feature normalization leads to better quality and reliability of signals, and enables the processing to be performed effectively while dealing with uncertainty. Equation (1) shows how this can be done based on statistics of the training data.

$$Y - Scored\ EMG_{e,g,j} = (EMG_{e,g,j} - \mu_{train,j})/\sigma_{train,j} \qquad (1)$$

In Equation (1), Y is the normalized output value denoting a standardized signal feature. $Scored$ denotes a standardized value normalization operation, EMG values of input signal features, e sample identifier for each signal instance, g refers to the identifier for the channel in the MIMO system, and j refers to the identifier for a particular signal feature. μ refers to the mean value indicating the average of the distribution of the data, $train$ indicates the training set used for the purpose of learning statistics, $\mu_{train,j}$ mean of feature j from training data, and σ standard deviation of feature j based on training data.

3.3 Feature extraction using DWT

An uncertainty-aware modular architecture for MIMO receivers is proposed to extract stable multi-resolution features from complex wireless signals. Using multiresolution decomposition, high-frequency noise is separated from low-frequency channel variations, improving feature stability and reliability. This enhances consistency in signal representation and supports more accurate equalization and decoding. The approach strengthens robustness under dynamic, noisy, and uncertain wireless channel conditions by ensuring stable feature extraction. As a result, the model achieves improved reliability and performance in complex communication environments.

$$DWT(n,m) = \frac{}{\sqrt{l2^n}} \sum_l e(l)\, \psi \left[\frac{m-l2^n}{2^n}\right] \qquad (2)$$

In Equation (2), $DWT(n,m)$ is the wavelet coefficient for signal information at scale n and location m in multiresolution analysis, where m is the location parameter that displays the wavelet's translation along the time axis. $e(l)$ an input signal sample value at a specific location l. Ψ decomposition uses the wavelet mother function. $\sum$ is a summation operator that is used for combining several signal samples, l indexing parameter for signal sample summation. $\frac{1}{\sqrt{2^n}}$ is a scaling parameter that ensures appropriate energy conservation. $\left[\frac{m-l2^n}{2^n}\right]$ the scaling and shifting parameter.

3.4 Uncertainty-Aware Modular using CSA-DBPNN

The objective of the CSA-DBPNN model, which adopts an uncertainty-aware approach for designing the modular MIMO receiver, is the decomposition process that makes the MIMO receiver works reliably in a highly unpredictable wireless environment. The CSA speeds up the convergence process by adapting the configuration of the MIMO receiver using exploration and exploitation processes. The DBPNN model captures the signal pattern. Identifies complex signal patterns to improve precision, flexibility, and stability in dynamic settings.

- **DBPNN for Uncertainty-aware adaptive prediction learning model**

To improve the functionality of the MIMO receiver using NN through optimal weight and bias tuning, an uncertainty-aware modular design is presented. The objective is to have an optimized parameter setting to avoid becoming trapped in local minima that hinder convergence during learning. By optimizing the parameter setting using global searches, the design can optimize signal detection and adaptability, which improves the model's overall performance, especially the signal equalization and decoding. To avoid becoming trapped in local minima that impede learning, the objective is to have an optimal parameter configuration. The architecture is able to maximize signal detection and adaptation by optimizing parameter settings through global searches. As a result, the model performs better overall, especially when it comes to signal equalization and decoding.

$$k = (m+1)o + (o+1)n \qquad (3)$$

In Equation (3), $k\ is$ the total number of trainable parameters, ensuring stability and effective learning when developing uncertainty-aware MIMO receivers. n the quantity of input neurons that use various channel contexts to describe signal properties. o the quantity of hidden neurons that consistently represent features. m the quantity of output neurons that reliably identify signals. $(m+1)o$ Decision-making neurons receive parameters from hidden neurons. $(o+1)n$ Input neurons' parameters to hidden neurons that consistently represent features.

$$e = 1/(1+F) \qquad (4)$$

In Equation (4), $e\ is\ the$ error measure that expresses the system's dependability and performance in terms of uncertainty in MIMO receiver processing. F Performance function based on the goal, demonstrating the accuracy of signal recognition under ambiguous channel conditions, $1/(1+F)$ a function that guarantees a gain in performance is correlated with a decrease in error.

$$O_j = e_j / \sum_{j=1}^{t} e_j \qquad (5)$$

Let equation (5), O_j normalized output based on the uncertainty-aware MIMO receiver's wise decision-making e_j performance/Error metric for the j the output under different channel circumstances. $\sum$ summation operator, $\sum_{j=1}^{t} e_j$ to guarantee balanced normalization, the total error across all outputs is summed in Equation (6).

$$W_1' = fW_1 + (1-f)W_2 \qquad (6)$$

$$W_2' = (1-f)W_1 + fW_2 \quad (7)$$

In Equation (7), W_1' optimized weight for MIMO receiver learning which ensures stability and reliability despite the uncertainty in the wireless environment. f is the ratio responsible for determining how much the initial weight and alternate weights contribute to learning. W_1 is the original weight that mapped the signals before optimization, $W_2'$and W2 is another weight that gives insight into how signals are mapped. $(1-f)W_2$ enhances learning through adaptability to wireless environmental change. In Equation (8), W_2' adaptation and stability within MIMO receiver operation in a random channel condition are made possible through the modified weight.

- **CSA for Global optimization of NN**

To improve parameter tuning when creating uncertainty-aware MIMO receivers, CSA is employed in a population-based optimizer. The capuchin monkey social structure serves as an inspiration for CSA. Candidate solutions are divided into leaders and followers in this algorithm. Leaders are responsible for steering the optimization process in the direction of the best signal processing setups. However, the leaders' guidance is different. To better balance local and global searches, CSA uses adaptive searching strategies.

$$w_{j,i} = \lambda_i + \frac{o_{ae}(u_{ji})^2 * sin(2\theta)}{h} \; j < \frac{m}{2} \quad (8)$$

In Equation (8), In the case of MIMO receivers that adapt to the uncertainties present, $w_{j,i}$ is the weighting factor between the two nodes j and i indicating the adaptive nature of the signal strength. λ_i is a constant weighting factor ensuring consistent signal training in a noisy and uncertain channel. An adaptive parameter uncertainty-based MIMO receivers. e the error parameter of the signal processing process within noisy and dynamic environments. o the optimization parameter, which is responsible for optimizing signal processing features. u interactions between input signals and characteristics of MIMO systems, h, the constant used to normalize the scaling of weights. $o_{ae}(u_{ji})^2$ scaling factor for adaptive enhancement of the signal feature amplitudes,$sin(2\theta)$ Modulation factor that enhances signal feature diversity. m represents the total population size.

$$u_{j,i} = \tau u_{j,i} + b_1\left(kbest_{ji} - w_{j,i}\right)q_2 + b_2(\lambda_i - w_{j,i})q_3 \quad (9)$$

In Equation (9), $u_{j,i}$ adapted Signal Relationship Strength, τ memory parameter is used for preserving the prior interaction value, b_1 learning Coefficient that the Optimal Candidate Solution affect the process, k Number of Parameters Used in Learning Processes, or Model Index, $best_{ji}$ optimal reference value for signal representation optimization, q_2 Scale Factor for adjusting the Best Solution Guidance, b_2 the Adaptation Coefficient for determining the effect of Global Weight Tendency, λ_i Base Weight Value which guarantees stability in learning process. q_3 Scale Factor that determines deviations from base recommendation.

$$w_{j,i} = \frac{1}{2}\left(w_{j,i}' + w_{j-1,i}\right) n/2 \le j \le m \quad (10)$$

In Equation (10), $w_{j,i}$ is the updated weight that is used to ensure signal stability and consistency in the feature extraction process, $w_{j,i}'$ optimizes the weights to accurately represent the relationship between signals, $w_{j-1,i}$ are weights from the previous layer representing the learning history of the model, n start index, m end index of the neuron range. The CSA-DBPNN algorithm is presented in Algorithm 1 for designing an MIMO receiver under uncertainty conditions. First of all, the loading of the dataset with Min-Max normalization method is done to stabilize signal variations. DWT can be utilized to achieve multi-level analysis, if needed. After initialization of DBPNN, optimization of the weights is done by employing CSA, with leaders guiding the followers.

Algorithm 1: CSA-DBPNN for Uncertainty-Aware MIMO Receiver Optimization

Input: MIMO signal dataset X

Output: Optimized parameters (W^*, b^*), predicted output $\hat{y}$

Step 1: Load the MIMO dataset containing noisy channel observations.

Step 2 (Normalization):

$$x' = \frac{x - min(x)}{max(x) - min(x)}$$

Step 3 (Feature Extraction): Apply optional DWT to obtain multi-scale features:

$$DWT(n,m) = \frac{1}{\sqrt{2^n}} \sum_l e(l)\psi\left(\frac{m - l2^n}{2^n}\right)$$

Step 4: Initialize DBPNN with random weights $W$and biases b.

Step 5: Initialize CSA population of candidate solutions $(W, b)$and compute fitness:

$$F = \frac{1}{1 + e}$$

Step 6 (CSA Optimization): Update solutions using leader–follower strategy and weight smoothing:

$$W_t = \frac{1}{2}(W_t' + W_{t-1})$$

Step 7: Select best solution if $F_{new} < F_{old}$.
Step 8: Train DBPNN using optimized parameters.
Step 9 (Prediction):

$$\hat{y} = DBPNN(X; W^*, b^*)$$

Step 10: Return Result
Return optimized CSA-DBPNN model with improved

4. Result and Discussion

The proposed CSA-DBPNN-based MIMO receiver presents an effective approach for integrating signal processing and DL modules, enabling reliable and efficient detection under uncertain wireless conditions. The model is implemented using Python and evaluated on a Windows platform with an Intel® Core™ i7 processor, ensuring accurate predictions and robust performance.

Latency (ms): The term for the delay required for the identification and processing of the MIMO signals, and its value shows the sensitivity of the uncertainty-aware modular receiver. **Throughput (Mbps):** Represents the maximum speed at which the data can be transmitted through different channels. **Packet Loss Rate** (%): Denotes the proportion of incorrect symbol detection, revealing the reliability of the system itself. **Feature Entropy:** Implies uncertainty-aware learning through the value of entropy or uncertainty associated with the feature extraction of the signals.

Performance evaluation using various metrics: The performance of all previous approaches, such as Residual Signal Network (RS-NET) [14], Time Division Duplex Multiple MIMO (TDD-MIMO) [15], and Deep Neural Network MIMO (DNN-MIMO) [16] was trained using the MIMO Receiver Reliability dataset that considers aspects of channel uncertainty, noise diversity, and parameters of receivers' reliability. Table 2 and Figure 3 show that the performance of the proposed CSA-DBPNN approach is better than the performance of other approaches concerning all the mentioned characteristics. Its latency is 9.2 ms, its throughput is 135.8 Mbps, its packet loss rate is 1.4%, and its feature entropy is 0.91.

Table 2: Performance Comparison of MIMO Receiver Models Under Uncertainty Conditions

Methods	Latency (ms)	Throughput (Mbps)	Packet Loss Rate (%)	Feature Entropy
RS-NET	18.5	85.2	4.8	0.72
TDD-MIMO	15.3	102.6	3.9	0.78
DNN-MIMO	12.7	118.4	2.6	0.84
CSA-DBPNN [Proposed]	9.2	135.8	1.4	0.91

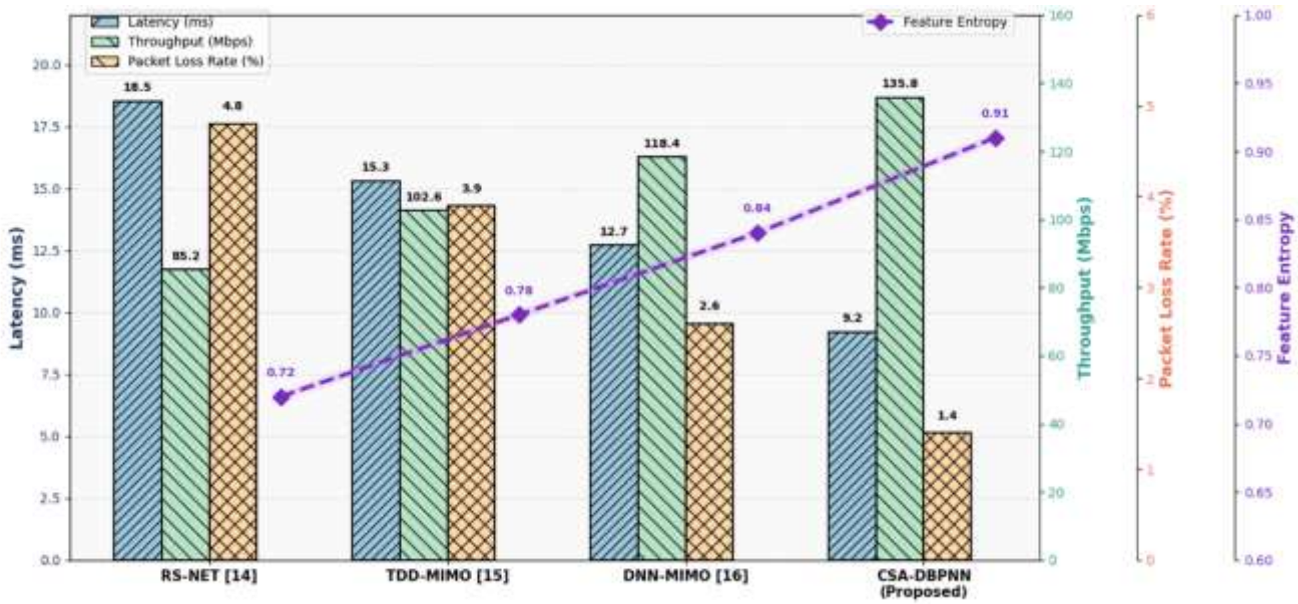


Figure 3: Performance Comparison of Uncertainty Aware MIMO Models

When evaluating uncertainty-aware MIMO receiver performance, existing models such as RS-NET, TDD-MIMO, and DNN-MIMO show limitations in balancing latency reduction, throughput enhancement, and robustness under noisy channel conditions. However, by integrating CSA optimization with DBPNN, the proposed CSA-DBPNN effectively improves convergence, reduces packet loss, and enhances feature representation, achieving superior overall communication performance under uncertain wireless environments.

5. Conclusion

The suggested CSA-DBPNN model effectively addresses the issues that arise with the conventional MIMO receivers because of the uncertainty and dynamicity of the wireless environment, and due to the use of an uncertainty-aware modular approach. Z-score normalization is performed before training to achieve uniform feature scaling. PCA is used in a procedure to reduce redundancy and irrelevance by selecting features. The method can consistently detect signals while reducing the number of inaccurate predictions it makes by integrating DL modules with uncertainty estimates. Additionally, using the CSA leads to better network convergence and increased learning capacity. With latency, throughput, packet loss rate, and feature entropy of 9.2 ms, 135.8 Mbps, 1.4%, and 0.91 respectively, the suggested method performs admirably. The integration of these techniques further strengthens the robustness and adaptability of the model under varying channel conditions. It also ensures improved decision-making reliability in complex wireless environments. However, the proposed model is difficult to execute in real-time due to its high computational complexity and requirement for high-quality observations, which might limit its deployment in large-scale current time systems.

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