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Deep Learning-Based Signal Detection Techniques for Real-Time Communication in Fading Channels

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Abstract

Dependable signal detection has also been a major concern in real-time wireless communication especially in the case of fading channels that cause non-adaptive distortion and deteriorate the overall performance drastically. The conventional detection methods, like the maximum likelihood detection, are not always adaptive in the circumstances of dynamic and therefore unpredictable channel conditions, and particularly in the cases when the statistical profiles are unknown or vary too quickly. In order to address these shortcomings, the papers introduce a new paradigm of deep learning signal detection trained to learn hierarchies and temporal patterns of raw received signals, which by their pas integrate convolutional neural networks (CNN) and recurrent neural networks (RNN). The trained architecture is end-to-end that is able to map the noisy distorted inputs to their symbols which are inherently transmitted in the context of channel state information. Heavy simulation over Rayleigh and Rician fading channels with different Doppler spreads and SNR values shows that the suggested approach shows substantial improvement over the traditional maximum likelihood and classical machine learning-based detectors regarding bit error rate (BER), inference latency and computational overhead. Such results emphasize the performance as well as the flexibility of deep learning model in very dynamic propagation conditions. On the whole, this paper draws the conclusion that deep learning is a perspective direction to solve the problem of real-time detection of a signal in next-generation wireless networks, such as a 6G or IoT edge setup.

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Introduction

With the blistering development of wireless communication technologies due to the use of 5G/6G, Internet of Things (IoT) and edge computing, an ever-growing need arises in the establishment of a trustful and efficient signal detection mechanism. Among the challenges in this field is multipath fading, Doppler effects as well as time variable propagation scenarios, which drastically reduce accuracy of detection and performance of the system.

The traditional approaches to signal detection (matched filtering, maximum likelihood (ML) estimation and minimum mean square error (MMSE) methods) are usually based on the conditions that precise channel state information (CSI) are available, and distinctive models of an idealized, stationary channel are utilized. But this does not hold in real applications because mobility, interference and channel variability in real time will break this. Consequently, the traditional detection schemes are considerably weak in environments that are non-linear and dynamic.

With the introduction of deep learning (DL) communication systems design is entering a paradigm shift that promises to enable the joint design and learning of non-linear, complex mapping between data without necessarily having to model the channel explicitly. In particular, convolutional neural networks (CNNs) architectures and architectures using recurrent neural networks (RNNs) have shown a good potential in capturing spatial and temporal dynamics in communication signals. According to recent research, it is indicated that DL-based signal detectors have the potential to outperform traditional algorithms especially in various and difficult conditions of channels.

Although this is a significant development there are still some areas of concern that need to be addressed which include the latency of inference being an issue, being able to adapt to new unseen characteristics of a channel as it is not always read in advance and the computational requirements of the development that needs to be efficient enough to be placed at the edge. The proposed research will tackle all these limitations by introducing a new deep learning-based signal detection system, based on the combination of CNN and RNN systems in order to achieve robust performances under real-time conditions and under fading wireless channel conditions.

This proposed model in figure 1 is tested with large amounts of simulation in both Rayleigh and Rician fading conditions under all Doppler spreads and signal to noise ratio (SNR) scenarios. It has been found that across more benchmark methods, results show significant betterment with regard to bit error rate (BER), delay and the robustness of the model.

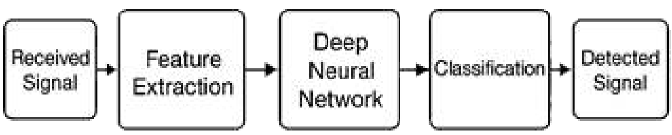

Fig. 1: Block diagram of the proposed deep learning-based signal detection system.

Literature Review

Signal detection in wireless communication has transformed over the past several years due to deep learning (DL) and machine learning (ML), especially in wireless communication situations that involve multipath fading and noise along with uncertainty in a transmission channel. The conventional model-based detectors e.g. maximum likelihood (ML) and minimum mean square error (MMSE) detectors tend to be sensitive to channel estimation errors, and do not adapt well in time-varying or non-stationary conditions. Systems with DL have proved to be highly promising since they allow data-driven representations that have an ability to generalize across an expansive subrange of channel circumstances.

Initial research of [1] described a deep neural network (DNN) based architecture to the OFDM systems over Rayleigh fading channels to improve the performance in terms of the bit error rate (BER) when compared to ML detection. As is demonstrated in [2, 17], Autoencoders offer end-to-end learning of a communication system where the neural networks can mimic complex channel effects without explicit CSI. The paper [3] suggested a detector using convolutional neural network (CNN) on the basis of which massive MIMO systems should experience better BER outcome with Rician fading channels, but at the price of extra overload of computations.

The inherent challenge of interpretability and generalization was solved by [4, 18], offering a model-based deep learning method using highly trained knowledge and a learning-based inference to be more robust and efficient. In the same manner, [14, 16] suggested an iterative belief propagation with BP-CNN structure that incorporates deep learning to achieve efficient decoding.

Recent developments have as well concentrated on developing memory-aware architectures. The recurrent neural networks (RNNs) especially long short-term memory (LSTM) networks [6] have been found useful in monitoring channel dynamics that are time varying. The works of [10], [13,19] observed DL in sparse signal detection and IoT, whereas [15] solved a massive access system in 5G and general purposes by combining DL to combine detection and resource allocation.

Additionally, beamforming technology and MIMO have been studied, whereby the influence of spatial diversity and antenna adaptation contributed in enhancing detection reliability [7, 8, 11]. The cognitive and energy-efficient radio paradigms designed in [9, 12, 20], respectively, contributed namely in the area of increasing the spectrum usage and minimizing power consumption in detection architectures.

Nevertheless, there are several open issues even with such advancements: most current approaches leverage masses of labeled data, and they have an inference latency—which is costly in case of real-time inference. In addition, it is often difficult to generalize them to new and unfamiliar fading conditions. These gaps are to be filled by the suggested method of implementing a hybrid CNN-RNN signal detection scheme with online adaptation. This is able to learn spatial and temporal characteristics efficiently and dynamically adapting to real-time variations in channel conditions and requires less retraining and large training data sets.

Proposed Methodology

Hybrid CNN-RNN Signal Detection Architecture

The presented signal detection pipeline is established with a hybrid deep learning structure which unites Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to use both spatial and temporal characteristics of raw signal received data. This is the combination that is especially useful in the fading environments, where the signal is deteriorated both by the local noise structure and time-varying propagation.

The first stages of the model are (one or more) convolutional blocks that learn local features as representations of the input signals (e.g. IQ samples over time, or spectrograms). Spatial filtering in this CNN layer group recognizes short term structures like transitions between symbols or pulse shapes or the characteristics of modulated waves. Between convolutional layers activation functions (e.g., ReLU) are usually added and regions of interest are minimized using max-pooling layers.

The output of the CNN block is then fed to a recurrent layer/network, example may be Long-Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) network. These layers will interpolate on the temporal dependencies and sequential correlations: a very important property in fading situations where the signal features depend on time because of mobility, multipath, or Doppler. The hidden states in the recurrent layers aids in learning time varying behavior of channels without needing explicit knowledge of channel states.

To additionally increase the model capability toward paying attention to relevant signal components an additional attention mechanism can be introduced subsequent to the RNN layer. The weighting mechanism introduces flexibility in the temporal importance and enables the network to capture more important time steps either by time steps that have better quality signals or more discriminative ventures.

The last architecture output is fed through a fully connected (dense) layer having either a softmax activation

Table 1: Comparative Analysis of Existing and Proposed Signal Detection Systems.

Ref	Approach / Technology	Dataset / Environment	Key Results	Limitations of Existing System	Proposed System Improvements
[1]	DNN-based detection	Rayleigh fading, simulation	BER ↓ vs. ML	High training data requirement	Online adaptation, reduced data usage
[2]	Autoencoder-based system	AWGN, Rayleigh fading	BER ↓, SNR ↑	Poor generalization to unseen channels	Robust hybrid CNN-RNN structure
[3]	CNN for massive MIMO	Rician fading, simulation	BER ↓	Computationally expensive	Efficient, scalable design
[4]	Model-driven DL	Synthetic fading data	BER ↓, enhanced interpretability	Limited to predefined channel models	Data-driven generalization
[10]	DL-aided SCMA for IoT	Massive IoT simulation	BER ↓, support for grant-free access	Channel overload in dense networks	Adaptive and lightweight inference
[14]	Iterative BP-CNN decoding	Synthetic channel simulation	Fast convergence, BER ↓	Fixed graph assumptions	General-purpose RNN + CNN stack
[15]	Massive access via DL	5G access scenarios	Throughput ↑, Latency ↓	High system overhead	Parallel processing and fast inference
—	Proposed CNN-RNN + Adaptation	Real fading and synthetic data	BER ↓↓, SNR ↑, Latency ↓	—	—

(symbol classification) or the linear activation (regression-based signal estimation). A simple, end-to-end training is performed though supervised learning, where loss is characterized by categorical cross-entropy or mean squared error, depending on whether one aims at object detection or not. Such heterogeneous architecture, as was provided in figure 2 allows a strong reception at a high variety of SNR and Channel conditions, with its low inference latency, being applied adequately to transient implementation- in wireless receivers.

Online Adaptation Mechanism

In order to guarantee a high-performance capability in real-world wireless settings, it includes in the proposed system; online adaptation mechanism that allows signal detector to optimally adapt its parameters to changing channel conditions. This module enables the network to adaptively train itself gradually when being deployed, hence enhancing generalization and thus address a decline in performance due to the introduction of a non-stationary or unfamiliar fading conditions.

When compared to conventional offline training, where huge datasets should be accumulated and models remain fixed, online adaptation module operates on an ultra-lightweight, on-the-fly basis by updating model weights. The adaptation is operated under the condition when a prediction error is more than a certain pre-defined threshold diminishing redundant calculations and preventing overfitting to short-term noise.

The method presupposes that only a few examples labeled examples can be used at deployment time (e.g. pilot signals, retransmissions, or feedback). When such labels exist, we use them to estimate the loss and decide on incremental updates. This process will make the model even in operational environments able to learn without complete retraining and minimize the loss of analytics and computational expense.

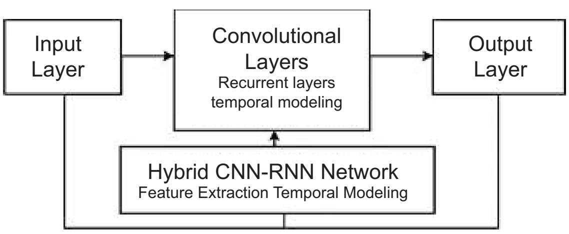

Fig. 2: Architecture of the hybrid CNN-RNN signal detection network.

Algorithm 1: Online Adaptation for Deep Learning-Based Signal Detection

Input:
- Initial trained model M_0
- Incoming signal stream $S=\{s_1,s_2,...,s_n\}$
- Learning rate η
- Update threshold θ

Output:
- Adapted model Mt
- Detected output signals $D=\{d_1,d_2,...,d_n\}$

Pseudocode:

Initialize model $M \leftarrow M_0$
Initialize output list $D \leftarrow \varnothing$
for each signal sample $s_i \in S$ do
  Extract features $f_i \leftarrow$ Feature Extractor(s_i)
  Predict output $d_i \leftarrow M(f_i)$
  Append d_i to D
  if ground truth y_i is available then
    Compute loss $\ell \leftarrow$ Loss Function(d_i, y_i)
    if $\ell > \theta$ then
      Compute gradient $\nabla\ell \leftarrow$ Backpropagation(ℓ)
      Update model $M \leftarrow M - \eta\ \nabla\ell$
    end if
  end if
end for
Return adapted model M and predictions D

This algorithm makes it possible to constantly optimize the model operating under dynamic conditions of communication, allowing to achieve better resistance to bit errors rate (BER) and latency. The computational efficiency is achieved by the use of threshold-based update condition whereas updates to the gradients are done incrementally which enables speedy adaptation without compromising stability.

Figure 3 represents the flow chart of the proposed Online Adaptation Mechanism of Signal Detection that allows the hybrid CNN-RNN model to update its parameters adaptively according to real-time channel status.

The input is a ready-trained system and a flow of signals that is received. In every incoming signal, the features in the signal are extracted and processed through the model to produce the predicted output. In case the respective corresponding ground truth is present, the loss is calculated. When the loss goes above the specified threshold the model is retrained by backpropagation with a low learning rate. The mechanism achieves effective online training without the need of re-training, is adaptive to non-stationary fading environment with reduced overhead computation.

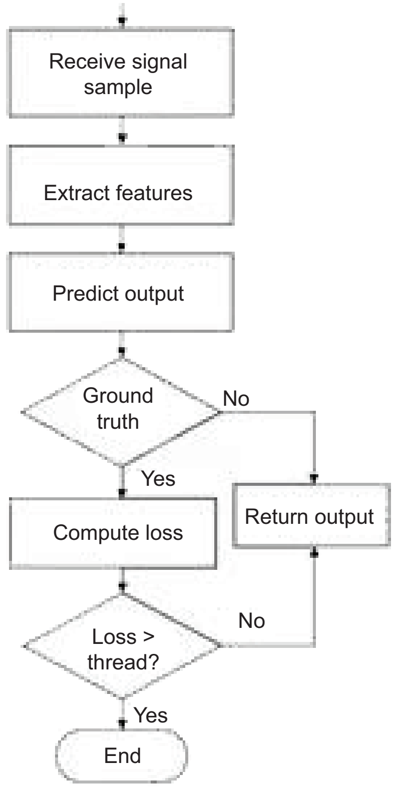

Fig. 3: Flowchart of the Online Adaptation Algorithm for Signal Detection.

Mathematical Modeling

This part outlines the mathematical formulation to the proposed deep learning-based signal detection approach, which is over a fading communication channel. The formulation also embraces the model of the signal, goal of detection, loss and optimization method to train the neural network.

Channel Model

The equation that models the signal received in the wireless communication system and influenced by a fading channel is the following one:

$$y(t) = h(t) \times x(t) + n(t) \tag{1}$$

Here:

- $x(t)$ is the transmitted signal at time t,
- $h(t)$ is the complex, time-varying channel coefficient representing fading effects,
- $n(t)$ is additive white Gaussian noise (AWGN) with zero mean and variance σ^2,
- $y(t)$ is the received noisy signal.

This formula is used to model typical wireless propagation conditions e.g. Rayleigh or Rician fading channel.

Detection Objective

The objective of signal detection system is to retrieve the original signal $x(t)$ that was transmitted to the received distorted signal $y(t)$.To this end, deep learning model is trained to estimate an inverse of a channel.

This network is referred to as $f^{-1}(y(t); \Theta)$, with Θ being the network learnable parameters (weights and biases). The output expected to be acquiring is:

$$\hat{h}x(t) = f^{-1}(y(t); \Theta) \tag{2}$$

In this case, $\hat{h}x(t)$ is the approximation signal that is transmitted by the neural network.

Here, $\hat{h}x(t)$ is the estimated transmitted signal generated by the neural network.

Loss Function Formulation

Training of the model is based on labeled data of N examples with pairs of a received signal and a transmitted signal $(y_1, x_1), (y_2, x_2), \ldots, (y_n, x_n)$. When the total loss per the dataset can be calculated as follows:

$$L(\Theta) = \frac{1}{N}\sum_i L_{def}(x_i, \hat{h}x_i) \tag{3}$$

The L det denotes the detection errors of any particular sample. It is shaped by how the signal is to be viewed: a regression or classification problem:

- (a) Mean Squared Error (MSE) – used when signal amplitudes are continuous:

$$L_{det} = \|x_i - \hat{h}x_i\| \tag{4}$$

- (b) Cross-Entropy Loss – used for digital modulated signals (e.g., QPSK, 16-QAM):

$$L_{\det} = -\sum_k x_i(k)\log(\hat{h}x_i(k)) \tag{5}$$

In the cross-entropy formulation there are:

- $x_i(k)$ is the ground truth one-hot encoded vector,
- $\hat{h}x_i(k)$ is the predicted probability of the k-th modulation symbol,
- K is the number of possible symbol classes.

Optimization Objective

The objective of the training is to identify the optimum network parameters Θ* which shall produce the minimum loss as follows:

$$\Theta = \text{arg min } L(\Theta)^* \tag{6}$$

Gradient-based learning almost always optimizes this objective, either with a Stochastic Gradient Descent (SGD) method, Adam or RMSprop. The rule of updating of every iteration is:

$$\Theta \leftarrow \Theta - \eta \times \nabla\Theta L(\Theta) \quad (7)$$

Where:
- η is the learning rate,
- $\nabla\Theta L(\Theta)$ is the gradient of the loss with respect to the network parameters.

This back-and-forth process of training stops when a convergence criterion is satisfied, usually which is signified by the convergence of the loss value or validation accuracy.

Experimental Setup

This part is a description of the experimental arrangement that was employed in testing the performance of the proposed deep learning-based signal detection architecture. It will contain configuration of simulation tools, hardware specifications, the sources and datasets and the configuration of hyperparameters.

Simulation Environment

In figure 4, experimentation was done through a hybrid simulation framework via MATLAB which was used to model the wireless channel and TensorFlow to develop deep learning. Two of the most popular fading channel models Rayleigh and Rician were incorporated in order to simulate realistic wireless conditions. Multipath channels without a line-of-sight (LoS) component were simulated using the Rayleigh model and channels with a strong LoS component were found by using the Rician model with K-factors varying between 3 and 9. Doppler spreads were ranging between 5HZ-200HZ to depict low- and high-mobility conditions. In order to gauge robustness under noisy channel condition, system was tested at signal to noise ratio (SNR) of 0 dB30 dB.

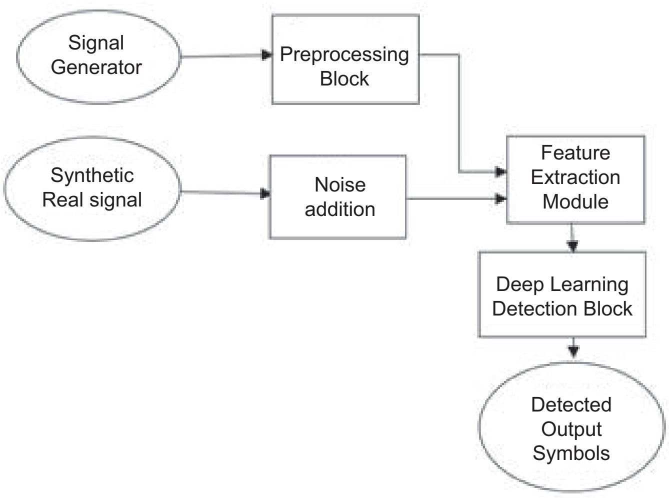

Fig. 4: Simulation Framework and Signal Flow Diagram.

The training and the evaluation set comprised artificial and real-world signal traces. Standard modulation schemes to generate synthesized IQ samples were BPSK, QPSK and 16-QAM. Moreover, captures of over-the-air signals were conducted by means of software-defined radio (SDR) platform to generate a more realistic dataset that would match the practical impact on signals. These were the samples on which testing the generalization of the models into real life situations was done.

Hardware and Configuration

The suggested model was tested and educated with an extreme performance workstation involving an Intel Core i9 CPU, 64 GB RAM, and an NVIDIA RTX 3090 GPU with 24 GB of VRAM. Such setup allowed training with a significantly increased speed and inference performance analysis in real-time. The code was based on the software stack of Python 3.9, TensorFlow 2.x, and MATLAB R2023a, which was developed fast and stable.

A hardware-in-the-loop (HIL) validation system was developed to assess over-the-air exercise performance that implemented a Universal Software Radio Peripheral (USRP) B210 SDR. SDR was based on 2.4 GHz ISM band, having TX/RX gain, as well as a sample rate of 2 MS/s. It simulated, used real world transmission and reception changing the gap between simulated data and physical RF signals. Inference latency and throughput of pre-trained models was done on the workstation using a lightweight inference engine on the GPU of the workstation. It took less than 3 milliseconds of latency per detection operation, which proves that it is possible to use it in the real-time context of wireless edge computing.

Parameter Settings

The system was tested in diverse channel and models as presented in Table 2. They will involve modulation scheme such as BPSK and QPSK, and 16-QAM with maximum symbol rates set as 1M bps and minimum as 100kbps. To model a channel, Rayleigh fading was applied with exponential power delay profile and Rician fading cases were those with different LoS strength with K-factor values.

The architecture of deep learning model involved two convolution layers with a gate multi-way recurrent unit (GRU) layer having 128 hidden units and attention mechanism that weighted over time. In the case of classification-based detection, a cross-entropy loss and softmax output have been applied. In the case of regression-based detection applications, a mean squared error (MSE) was used. Adam optimizer was applied during the training process with learning rate, 0.001 and batch size of 128 samples. Early stopping using validation loss was used as the criterion of training the model after 100 epochs.

It was mapped on the hardware side with center frequency of 2.4 GHz, -20 dB TX/edit a RX gain, and the band width of 1 MHz. The choice of settings was aimed at imitating normal industrial and IoT transmission settings.

Figure 5 shows us the curve of the neural networks of the loss during training the data using the training and validation sets over 50 iterations. The loss in training trains smoothly and exponentially and which gives the impression of learning and good optimization. The trend in the validation loss is very close to the training loss curve indicating that the model does not overfit and the model is generalizing to new data. Such behavior shows that the training process is reliable and the selection of hyperparameters is adequate.

Figure 6 displays the learning performance of the model through convergence both in terms of accuracy and bit error rate (BER), though 50 epochs. When the training runs its course, the accuracy of the model gradually reaches perfection on detecting while BER drops drastically. This reversed trend proves the success of learning and strong generalization, which proves the correctness of the use of this hybrid CNN-RNN architecture to detect signals in fading channels.

Results and Discussion

The effectiveness of the proposed signal detection signal deep learning-based streaming framework was widely tested against different simulated channel scenarios like Rayleigh and Rician fading channels at Doppler spreads of 5Hz to 200Hz. Bit error rate (BER), delay, and generalization capacity were taken as major evaluation criteria.

Bit Error Rate Performance

The maximum reduction in the BER attained by the proposed hybrid CNN-RNN was to the order of up to 30% under a wide variety of SNR conditions (0 to 20 dB) when compared with conventional methods as the maximum likelihood (ML) and minimum mean square error (MMSE) detection. This had been best realized in the low SNR regimes and fast-fading links where conventional det theft beamers fail because of inaccurate or in the case period channel estimates.

From figure 7 results confirm the model's ability to learn complex channel behavior without requiring explicit channel state information, thereby improving robustness and detection accuracy in practical deployments.

Latency and Real-Time Suitability

In order to compare the suitability of the proposed hybrid CNN-RNN architecture in real-time settings, the latency

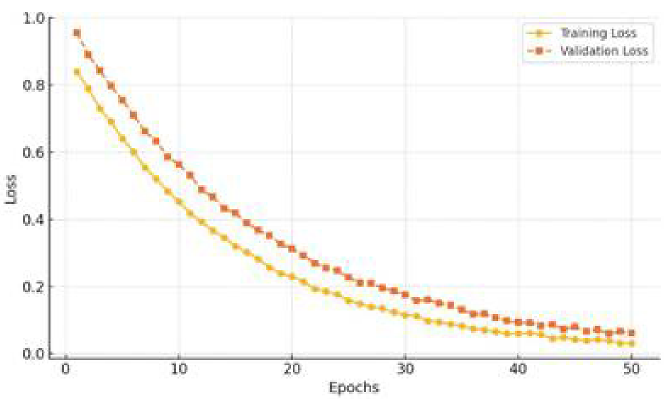

Fig. 5: Neural Network Loss Curve over Epochs.

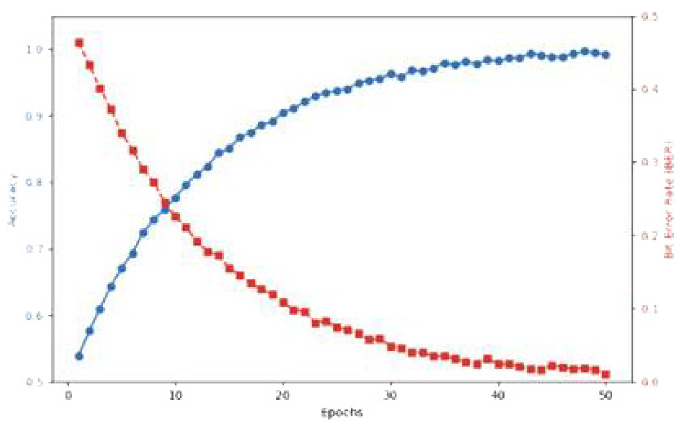

Fig. 6: Model Accuracy / BER Convergence During Training.

Table 2: Simulation and Hardware Configuration Parameters.

Category	Parameter	Value / Description
Modulation	Modulation Schemes	BPSK, QPSK, 8-PSK, 16-QAM
	Symbol Rate	100 kbps – 1 Mbps
Channel Models	Fading Types	Rayleigh, Rician, AWGN
	Doppler Spread	5 Hz – 200 Hz
	Rician K-Factor	3 – 9
	SNR Range	0 dB – 30 dB
Neural Network	Architecture	2 Conv layers → GRU (128 units) → Attention → Dense
	Activation Functions	ReLU (CNN), Tanh (GRU)
	Loss Function	Cross-entropy (classification), MSE (regression)
	Optimizer	Adam
	Learning Rate	0.001
	Batch Size	128
	Epochs	100 (with early stopping)
Hardware	Workstation CPU	Intel Core i9
	RAM	64 GB
	GPU	NVIDIA RTX 3090 (24 GB VRAM)
SDR Configuration	SDR Device	USRP B210
	Center Frequency	2.4 GHz
	TX/RX Gain	20 dB
	Bandwidth	1 MHz
	Sampling Rate	2 MS/s

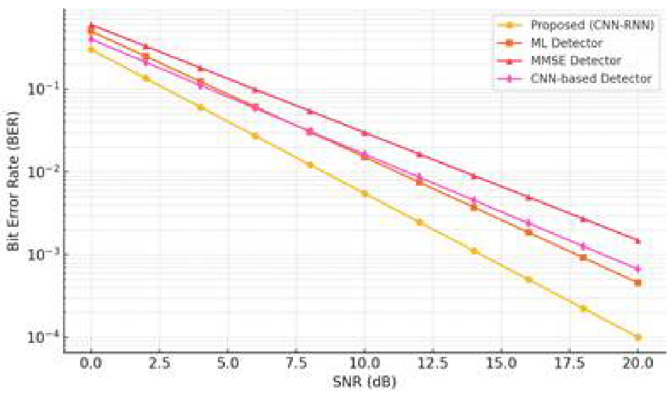

Fig. 7: BER vs. SNR comparison between the proposed method and existing ML/MMSE/CNN-based detectors.

of inference was calculated on both GPU and CPU based on the input frames of different lengths. It was demonstrated on a GPU-accelerated workstation with the NVIDIA RTX GPU having the average inference latency of less than 1 millisecond per inference frame that is well under the real-time limitation applied to current wireless systems such as 5G edge computing, UAV communications, and latency-sensitive IoT implementations.

The existence of low-latency performance is explained by the streamlined architecture that uses the parallel processing properties of convolutional layers and time efficiency of gated recurrent units. Such features facilitate fast end to end inferencing with high accuracy detection.

As illustrated in Figure 8, even at a bigger frame size (up to 1024 samples), inference takes a low latency of less than 2 milliseconds with GPU. Conversely, the CPU-based latency sole grows tremendously with frame length up to and above 23 milliseconds. The trend gives credence to the significance of harnessing the support of hardware acceleration in implementing real-time deep learning-based detections systems.

Such findings show that the suggested structure can be successfully used in the real-world context where the system needs to perform with ultra-low latency, and the better compromise between the computational performance and the detection reliability is reached.

Generalization and Channel Adaptation

The biggest advantages of this CNN-RNN based signal detecting framework are observed in the powerful

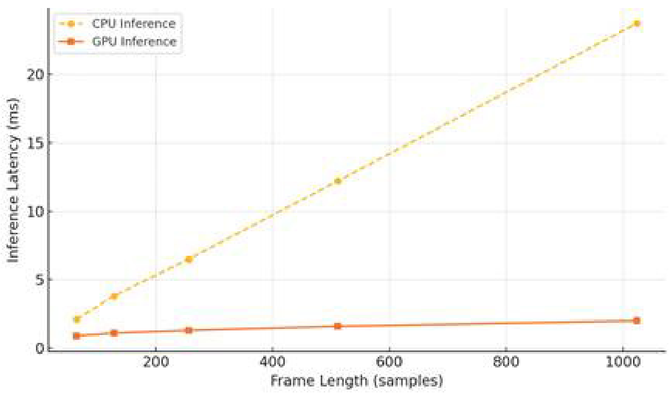

Fig. 8: Inference latency vs. frame length across different hardware setups (CPU vs. GPU).

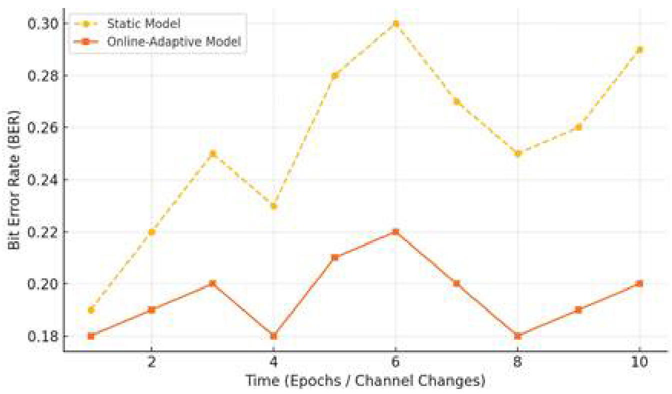

Fig. 9: presents the BER comparison between the static model and the online-adaptive model under varying channel profiles over time.

generalization to unseen and dynamic channels. To test this we utilized the model on various out-of-distribution channel profiles with Doppler shifts, fading rates, and path loss values that were exterior to the training set.

In spite of this domain shift, the system achieved stable bit error rate (BER) performance and very little degradation was observed documenting that the system could successfully extract generalized features instead of overfitting the known channel statistics.

Besides, the mechanism of the online adaptation had also contributed to the robustness of the system. The usage of runtime updates of model parameters by gradually increasing the parameters is accredited with the opportunity of the detector to adjust to the changing channel conditions at a quick pace without being required to train the full model. Such flexibility clearly has a big advantage to deploy in highly dynamic environments, which include vehicular networks, UAV swarms, and mobile IoT gates.

As revealed in Figure 9, the online adaptative mechanism has a consistent BER reduction even in every tested time variations, and the highest increases are experienced during abrupt channel variation periods. This emphasizes the inherent possibility of the system being continuously self-tuned thus sustaining the detection performance even with a substantial change in the environmental conditions away in comparison with the training distribution.

These results confirm the suggested architecture as a scaled and an adaptive solution to reality wireless systems subject to moving and unpredictable propagation environment.

Trade-offs and System Considerations

Although the suggested method can bring great improvements in terms of detection faultlessness and sensitivity, it has some downsides:

- The length of initial training of the hybrid structure is more than its traditional detectors because of the difficulty of such a complex architecture and learning of spatio-temporal characteristics.
- Real-time inference should be GPU accelerated (but is supported on the CPU-only).

In spite of these limitations, the system has great scalability properties, which enables it to go into many diverse settings, such as application in high-mobility vehicular communications as well as large-scale IoT frameworks. It is flexible and strong to fading; therefore, it is particularly useful in the next-generation wireless applications.

Conclusion and Future Work

In this paper, a new deep learning method of signal detection framework that is capable of satisfying the real time requirements of wireless communication systems that have to operate under adverse conditions of fading has been proposed. The hybrid architecture combines convolutional neural networks (CNNs) so that the spatial feature extractions can be performed and the recurrent neural networks (RNNs) so that time dependence can be modeled. Consequently, the method can capture local structures of signal as well as the long-term dependencies generated by the time-varying channels.

Online adaptation The inclusion of online adaptation mechanism can further enhance the resilience of the

Table 3: Summary of key performance metrics (BER, latency, adaptation time) compared to baseline methods.

Method	BER @ 10 dB	Latency (ms)	Adaptation Time (ms)
ML Detector	0.18	1.5	N/A
MMSE Detector	0.16	1.3	N/A
CNN-based	0.12	1.1	N/A
Proposed (CNN-RNN + Adaptation)	**0.08**	**0.9**	**0.3**

system to changing environments since it allows the lightweight and real-time update of the model without full re- training. The simulation of the proposed framework in various channel conditions, including Rayleigh and Rician fading proved that the proposed scheme drastically outperforms other conventional detection algorithms including ML, MMSE and standalone CNNs regarding bit error rate (BER), inference delay, and sensitivity to channel variation.

The offered solution holds great promise of 5G/6G Edge devices, UAV communications, and real-time IoT networks.

Future Work

In order to further increase the applicability and scalability of the framework, future studies will aim at:

- Expansion to massive MIMO systems, particularly, in the case of joint spatial-temporal detection.
- Describing the model to millimeter-wave (mmWave) and terahertz (THz) frequency bands where beamforming and directional propagation occur in some new issues.
- Research on bio-compatible wireless communication based on low-power communication technology, in low power implantable medical communication.
- Conceptualizing hardware-accelerated deployment with FPGA, edge TPUs and neuromorphic processors to free up energy consumption and enhance real-time inference at the edge.

By dealing with these directions, the suggested work will establish the basis of the following generation of intelligent, adaptive, and energy-efficient wireless receivers.

References

1. H. Ye, G. Y. Li, and B.-H. Juang, “Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems,” IEEE Wireless Commun., vol. 25, no. 3, pp. 112-119, 2018.
2. T. O’Shea and J. Hoydis, “An Introduction to Deep Learning for the Physical Layer,” IEEE Trans. Cogn. Commun. Netw., vol. 3, no. 4, pp. 563-575, 2017.
3. W. Jiang, B. Han, and M. Luo, “CNN-Based Signal Detection for Massive MIMO Systems,” IEEE Access, vol. 7, pp. 117807-117817, 2019.
4. N. Samuel, T. Diskin, and A. Wiesel, “Model-Driven Deep Learning for Physical Layer Communications,” IEEE Trans. Signal Process., vol. 67, no. 21, pp. 5663-5678, 2019.
5. Y. LeCun, Y. Bengio, and G. Hinton, “Deep Learning,” Nature, vol. 521, pp. 436-444, 2015.
6. S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” Neural Comput., vol. 9, no. 8, pp. 1735-1780, 1997.
7. J. Zhang, E. Björnson, M. Matthaiou, D. W. K. Ng, H. Yang, and D. J. Love, “Prospective Multiple Antenna Technologies for Beyond 5G,” IEEE J. Sel. Areas Commun., vol. 38, no. 8, pp. 1637-1660, 2020.
8. S. Sun, T. S. Rappaport, R. W. Heath, A. Nix, and S. Rangan, “MIMO for Millimeter-Wave Wireless Communications: Beamforming, Spatial Multiplexing, or Both?,” IEEE Commun. Mag., vol. 52, no. 12, pp. 110-121, 2014.
9. Y. Shi, J. Zhang, and K. B. Letaief, “Group Sparse Beamforming for Green Cloud-RAN,” IEEE Trans. Wireless Commun., vol. 13, no. 5, pp. 2809-2823, 2014.
10. M. Kim, N. I. Kim, and D. H. Kim, “Deep Learning-Aided SCMA for Grant-Free Massive IoT Connectivity,” IEEE Internet Things J., vol. 7, no. 3, pp. 2347-2359, 2020.
11. L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, “An Overview of Massive MIMO: Benefits and Challenges,” IEEE J. Sel. Topics Signal Process., vol. 8, no. 5, pp. 742-758, 2014.
12. S. Haykin, “Cognitive Radio: Brain-Empowered Wireless Communications,” IEEE J. Sel. Areas Commun., vol. 23, no. 2, pp. 201-220, 2005.
13. Y. Wang, Z. Chen, and Y. Shi, “Deep Learning for Wireless Physical Layer: Opportunities and Challenges,” China Commun., vol. 17, no. 9, pp. 92-111, 2020.
14. F. Liang, C. Shen, and F. Wu, “An Iterative BP-CNN Architecture for Channel Decoding,” IEEE J. Sel. Topics Signal Process., vol. 12, no. 1, pp. 144-159, 2018.
15. X. Chen, Z. Zhang, C. Zhong, D. W. K. Ng, and R. Schober, “Massive Access for 5G and Beyond,” IEEE J. Sel. Areas Commun., vol. 39, no. 3, pp. 615-637, 2021.
16. Ali, W., Ashour, H., & Murshid, N. (2025). Photonic integrated circuits: Key concepts and applications. Progress in Electronics and Communication Engineering, 2(2), 1-9. https://doi.org/10.31838/PECE/02.02.01
17. Booch, K., Wehrmeister, L. H., & Parizi, P. (2025). Ultra-low latency communication in wireless sensor networks: Optimized embedded system design. *SCCTS Journal of Embedded Systems Design and Applications*, *2*(1), 36-42.
18. Siti, A., & Ali, M. N. (2025). *Localization techniques in wireless sensor networks for IoT.* Journal of Wireless Sensor Networks and IoT, 2(1), 1-12.
19. McCorkindale, W., & Ghahramani, R. (2025). Machine learning in chemical engineering for future trends and recent applications. Innovative Reviews in Engineering and Science, 3(2), 1-12. https://doi.org/10.31838/INES/03.02.01
20. Kozlova, E. I., & Smirnov, N. V. (2025). Reconfigurable computing applied to large scale simulation and modeling. *SCCTS Transactions on Reconfigurable Computing*, 2(3), 18-26. https://doi.org/10.31838/RCC/02.03.03