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Deep Learning Techniques For Massive MIMO Detection Algorithms: A Review

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Abstract

Massive Multiple-Input Multiple-Output (MIMO) is a critical Technique for next-generation communication systems, as it significantly improves spectrum efficiency and system capacity, that must meet user performance and quality of service requirements(QoS). However the detection of signal in massive MIMO systems remains challenging due to the limited performance of traditional algorithms and high computational complexity. Over recent years deep learning has been introduced as a method for improving signal detection algorithms in massive MIMO systems .This study provides a systematic review of Deep neural network-based detection techniques for massive MIMO systems .A systematic literature review was conducted, drawing on recent studies selected from major scientific databases and research published between 2016 and 2025, with a focus on widely adopted detection frameworks. A unified comparison was performed using key criteria, including bit error rate (BER) performance, computational complexity and practical feasibility. The reviewed methods were categorized as data-driven, model-driven, and hybrid approaches, allowing for the organization of analyses according to their design principles. The results indicate that model-driven and hybrid techniques enhanced trade-off between detection accuracy and computational complexity, while purely data-driven methods require intensive training and exhibit limited generalize ability under varying channel conditions. Compared to existing surveys, this work provides a more standardized classification and a more accurate comparative framework, highlighting current research trends and identifying existing challenges, such as scalability for large-scale systems ,effective training strategies and robustness to realistic channel environments.

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1. INTRODUCTION

Wireless communication technologies have advanced significantly in everyday life as a result of market demand and technological improvement. Wireless network communication has advanced dramatically from 1G to 5G [1, 2]. Wireless communication systems must be capable of supporting a larger number of users, varied forms of traffic, and multiple applications and access technologies [3, 4]. Massive MIMO technology uses a huge number of antennas to boost data rates ,coverage and performance of the network. Massive MIMO Enhances network capacity and spectral efficiency by allowing multiple users to communicate simultaneously, which is critical to accommodate the increasing requirement for high-speed connectivity in the 5G network and beyond. Notwithstanding their potential huge MIMO systems' increasing complexity creates a considerable obstacle to fully exploiting these advantages. The Integration of high-order modulations and huge numbers of antennas in particular, considerably complicates efficient signal detection, making detection of perfect maximum likelihood (ML) detector computationally infeasible [5]. As a result, developing low complexity and effective symbol detector is critical to make massive MIMO practicable for Practical applications [6].

There has been a substantial effort into creating effective MIMO detectors. These techniques are broadly classified as iterative , linear and learning-based detectors. While linear detectors, such as zero-forcing (ZF) and minimum mean-square error (MMSE) are simple and work do well in small-scale systems, they fall short when high-order modulations and huge numbers of antennae are used. Iterative detectors, such approximation message passing (AMP), orthogonal approximation message passing(OAMP), and expectation propagation, attempt to nearly ML performance via iterative processes [7]. Orthogonal AMP (OAMP), for example, delivers this increased robustness while requiring more extensive computations since calculations of inverse matrices are required in every cycle [6].

Artificial intelligence (AI) assisted multiple-input multiple -output (MIMO) Laying the groundwork for the Improvement 6G wireless communication networks. Being able to support a high number of transmitted and received antennas ,MIMO Technique enables beyond-5G technology to support consumer requirements of high data speeds. Nevertheless, multiple transmitted and received antennas, mean the detection of the signal at the receiver end is a complicated task. To address the problem of identifying problem in MIMO technology [1], MIMO detection with the help of AI is a Major improvement in wire communication. The next generation of the wireless system can come as researchers apply the power of the deep learning algorithms to improve the performance of the MIMO systems. As the entire world transitions to the fifth-generation (5G) wireless networks, the assumption is that the full development of AI technology is not likely until the sixth-generation (6G) wireless networks roll out. In order to hasten the process of developing AI-enabled future wireless communication networks, research information related to AI methods will be essential to facilitate these networks in fulfilling diverse needs and in a broad range of applications [8, 9]. Consequently, the main goal of this research study is to analyze the current trends in AI-assisted MIMO detection in the implementation of physical layer networks in future wireless communication systems. Namely, this work makes the following contributions:

1. The study investigates into modern current AI based enhancements of enhanced MIMO detection techniques and its relevance in enhancing the effectiveness within 6G and beyond wireless communication systems
2. The problem of AI-aided MIMO detection systems are addressed in the studies
3. MIMO detection using AI technologies will make wireless networks of the next generation

The research will be organized as following, the second section provides a review methodology . section three provides a literature review and its Table, as well as a summary of the most important gaps in the reviewed research. Section four provides massive MIMO structure; fifth Section provides massive MIMO detection; Section six provides a fundamental of deep learning architectures for wireless communication system; and Section seven provides Deep learning-based Massive MIMO detection. The eighth Section provides a comparison between Massive MIMO detection and Massive MIMO detection-based DL; Section nine highlights the limitations and obstacles faced by Massive MIMO detection-based DL; and finally, Section ten provides the research's conclusion.

2. REVIEW METHODOLOGY

The methodology used in this review is comprehensive and aimed at having a complete and objective review of the deep learning techniques using in massive MIMO detection.

2.1. DATA SOURCES

The literature was collected in large scientific databases, such as IEEE Xplore, ScienceDirect (Elsevier), and Google Scholar. These databases have been chosen because they cover a wide research of wireless communications and signal processing.

2.2. SEARCH STRATEGY

The most relevant studies have been retrieved using a set of suitable keywords. These keywords include: Massive MIMO detection, Deep Learning in MIMO, MIMO signal detection, OAMP-Net, LSTM MIMO detection and AI-based wireless communication.

2.3. INCLUSION AND EXCLUSION CRITERIA

The inclusion criteria used: Conference papers and peer-reviewed journal articles, Research on detecting massive MIMO, research using deep learning methods.
The exclusion criteria were: Other studies that are irrelevant but not dealing with detection algorithms, Duplicate papers , Articles that are not technical enough.

2.4. TIME RANGE

The chosen articles were published in 2016-2025 to cover both old and new developments in the field of massive MIMO and deep learning technologies.

2.5. STUDY SELECTION PROCESS

The selection of the studies was done in several steps. The screening of titles and abstracts was done to eliminate irrelevant papers. Subsequently, full-text analysis was conducted to make sure that they are relevant and of quality. finally, the most important and the latest ones were chosen to be reviewed in more detail.

2.6. CLASSIFICATION AND EVALUATION FRAMEWORK

The chosen studies were divided into two basic categories:

1. Conventional massive MIMO detectors (e.g. ZF, MMSE, OAMP)

2. Deep learning-based detection methods (e.g., LSTM-based detectors, data-driven models, OAMP-Net).

The studies were analyzed in terms of the essential performance indicators like the bit error rate (BER), the computational complexity, the scalability, and the robustness in the presence of various channel conditions.

3. LITERATURE REVIEW

Aarujos in (2016) presented that more precise and less complex channel estimation algorithms of massive MIMO systems are needed, and it was also proposed that massive MIMO can be combined with small cells and D2D communication in the post-5G networks. This is an indication of the initial research works that dwelled on the scalability of the system and architectural efficiency, as opposed to the optimization of detection [10].

In (2017), the authors proposed a MIMO detector called DetNet, which is based on deep learning. In contrast to conventional detection models, DetNet was shown to be capable of dealing with fixed and varying channel conditions with just a single trained model, and this is a significant change towards data-driven detection methods [11].

In (2018) the researchers made another proposal of a model-driven deep learning network founded on iterative detection. as compared to purely data-driven models such as DetNet. The research will also be employed to refine the iterative detection process by training a few important parameters with the aid of deep learning [12] .

Mahmoud A. Albreem (2019) conducted a Systematic review of the MIMO detection Techniques and emphasizes the trade-off between computational complexity and performance . This research svalidate the limitations of traditional methods and encourages the use of more sophisticated methods like deep learning.[13].

M. Khani et al. in (2020) have presented MMNet, which is an iterative deep learning detector of a massive MIMO system. Compared to previous methods, MMNet has a more appropriate balance between performance and computational complexity, which is more appropriate in real-time applications with realistic channels [14].

The authors of (2020) also reviewed a range of MIMO detection algorithms and methods of their implementation. This paper gives a greater comparative view of the traditional and emerging detection methods [15].

S. Shahabuddin et al. (2020) address the issue of massive MIMO systems detection using matrices. The article contrasts computational complexity with the modern approximate matrix analysis methods. Among its greatest contributions is the fact that it gives design advice on how to implement VLSI under the limitations of different devices. Though the above approaches lead to lower computational complexity, they are not as efficient in large-scale systems, yet another reason why solutions based on deep learning are used [16].

The authors in (2020) introduce a (JCESD) Joint Channel Estimation and Signal Detection framework of MIMO systems. They present a deep learning detector OAMP-Net2, which is based on the OAMP method. This study has a significant contribution due to the low level of trainable parameters, therefore, in terms of training pace and reliability of the results obtained reinforcing the advantages of model-driven methods [17].

Mahmoud Albreem (2021) also added the shortcomings of classical detection methods in massive MIMO uplink systems and suggested using deep learning in combination with conventional signal processing of massive MIMO systems particularly the fifth generation network and beyond. This means that there is an increasing trend towards hybrid detection frameworks [18].

K. K. Vaigandla and D. N. Venu (2021) give an account of potential technologies, advantages, and prospects related to the massive MIMO technology along with a description of all the considerable issues, and this paper introduces some of the ideas of the massive MIMO network systems this work highlight existing limitations and identify open research problems [19].

Nguyen et al. (2022) have proven (DNN) deep neural network in detection algorithms of large MIMO systems can considerably decrease detection error and computation complexity and running time. This proves the power of deep learning towards large-scale MIMO systems [20].

Moreover, the study in (2022) was devoted to the antenna design of massive MIMO systems in 5G wireless networks. It is not directly related to detection, but emphasizes the issue of hardware limitations in the general performance of a system [3].

In (2023) the authors introduce the AMIC-NET network, which is a data-driven detection network of massive MIMO system in the transmission link. The simplification of the iterative algorithm into a spaced links deep network is one of the most important contributions to this paper to make it simpler [21].

The authors of (2023) provide full analytical research of detection Techniques in massive MIMO and MIMO systems. There are methods of detection which are classified in terms of their principles of operation. The overall contribution of the paper is to present the open research issues and future prospects of detection in Massive Multi-User MIMO systems particularly in scalability and performance trade-offs [22].

Mahmoud Albreem in (2023) proposed low-complexity detection algorithms of massive MIMO systems relying on ZF and V-BLAST. To some extent, Despite reducing complexity, but at the same time, they are based on traditional frameworks, and in highly complicated situations, they might be restrictive to performance [23].

The author in (2023) gives the problems that are emerging in Massive MIMO systems of the 5G and more networks. The key goal of this dissertation is to develop competitive receivers which are simple in nature at a high convergence rate and use of a combination of specialized knowledge and deep learning techniques This reflects a clear research trend toward hybrid and adaptive detection frameworks [24].

The authors in (2024) suggest AMP-DNN, a low-complexity detector using deep learning in massive MIMO systems Quick and stable training irrespective of modulation rank or the size of the antenna is one of the most important contributions of the paper [25]

In (2024) the authors diffusion-based detection methods were proposed, in which noise reduction is done with probabilistic sampling. This is a new trend that goes out of the traditional deterministic evaluating methods [26].

In (2025) the authors Proposes a NOMA-based Massive MIMO system with adaptive power distribution and an Infinity-Norm detector based on the ADMM which is initialized using a modified MMSE estimate, a move that is intended to enhance the detection accuracy and convergence speed. [27].

The authors in (2025) explore the application of artificial intelligence to realise ultra-large MU-MIMO systems at terahertz frequencies and address the key challenges in the development of transceivers. One of the greatest contributions of the work is that it presents three research directions on how to develop the unique algorithms of artificial intelligence to realis MU-MIMO systems at terahertz frequencies [28].

The authors of (2025) address the recent developments in ultra-massive MIMO methods in the classical spatial domain. As observed in the report, the trend towards taking the relevant technology in the conventional space domain to the beam domain is on the increase. Lastly, the challenges associated with ultra-massive MIMO communication systems in the future are touched upon [29].

In (2025), the authors provide a MIMO Net, which is a framework of detecting MIMO signals through deep learning that is lightweight. This study offers a novel architecture of a front-end neural network that balances the best location in the detection performance and complexity [8].

The authors in (2025) provide the signal detection methods using LSTM to massive MIMO systems, and three hybrid detectors. In order to enhance the level of accuracy, the paper has integrated conventional detection strategies with the LSTM networks. A major contribution of the paper is of reducing the computational complexity because it does not require matrix inversion and multiple repetitions [30].

Finally, recent works in (2025) [8], [28] [29] and [30] are on ultra-massive MIMO and 6G systems. In these studies, there is a growing importance of artificial intelligence in controlling the complexity of systems. Specifically, LSTM based detectors are better in dynamic channels, and lightweight neural networks are intended to find a balance between the level of detection and computational cost.

Table 1. Show The Summary Of The Literature Review

Ref	Research methodology	Main Findings	Strength	Limitations
[10]	A review - based analytical of massive MIMO technologies and system model	Improves energy efficiency ,system capacity and spectral efficiency	comprehensive survey including 5G solution and Key challenges	Leaves open challenges ,no suggested algorithm and lack validation
[11]	Design model driven DL detector (DetNet) using unfolded projected gradient descent for varying and fixed channels	Near - best accuracy and strong robustness to channel/noise variations with low complexity	performs well across channels without requiring SNR knowledge	Assumes perfect CSI and requires high training cost
[12]	This paper presents model-driven DL detector (OAMP-Net) by unfolding OAMP with few learnable parameters	enhances detection performance compared to OAMP under various MIMO channels with low complexity	In time-varying channels robust performance and Fast training	Requires accurate CSI and relies on OAMP assumptions
[13]	Comprehensive categorization of massive MIMO detectors (approximate , linear, nonlinear and ML based)	Linear detectors have low complexity, and advanced methods have higher performance at a higher cost.	offers systematic comparison highlighting complexity-performance trade-off	Does not include new method and is not evaluated in realistic large scale scenarios
[14]	Suggest model-driven DL (MMNet) by unfolded iterative soft- thresholding using channel correlations with online training	Attains near-optimal performance with lower complexity , surpasses OAMP Net and achieves 4–8 dB gain over MMSE.	A computationally efficient, hybrid, model-driven/data-driven design, with excellent performance on realistic channels	hardware implementation challenges remain ,online training adds latency
[15]	Comprehensive overview of MIMO detector with operational analysis and mathematical	Performance depends on method characteristics and no single detector achieves optimal complexity- BER trade-off	comparative analysis of modern and classical detectors with hardware implementation insights	Mainly theoretical review without simulations , no novel algorithm or experimental validation
[16]	comparative analysis of approximate inverse methods and matrix factorization techniques for massive MIMO detection	GS has low complexity but unstable performance , Cholesky/LDL offer balanced complexity-performance	offers practical complexity insights appropriate for VLSI implementation	limited evaluation on realistic channels and Performance changes with system configuration
[17]	Introduce Model-driven DL through OAMP unfolding (OAMP-Net2) with few parameters and joint channel estimation-detection (JCESD)	Attains better performance than OAMP and other deep learning detectors with low parameters and fast training .	Model knowledge can be readily combined with DL to achieve high performance and robustness and to also reduced training cost.	It sensitive to realistic channel conditions and is based on assumptions such as unitarily-invariant channels.
[18]	Review and classification of deep learning MIMO detectors (e .g OAMP-Net , ADMM ,DetNet , CNN , hybrid models)	Deep learning detectors attain close to optimal performance with intermediate complexity but degrade in high order modulation and realistic channels	Presents comparative analysis of deep learning detector in term of complexity , performance and implementation	Preliminary evaluation in realistic conditions primarily tested on simplified channel models
[19]	Survey study of massive MIMO	Improved energy and	Well-organized	Does not deeply analyze

	including channel estimation, detection , precoding, and uplink/ downlink models	spectral efficiency, constrained by pilot contamination , CSI complexity, and hardware challenges	discussion combining theory , system models and enabling technologies	advanced deep learning detection methods and lacks quantitative evaluation
[20]	Survey of model-driven DNN detection through unfolded iterative algorithms (e.g., OAMP-Net2 , DetNet, MMNet)	Deep neural network detectors reduce runtime complexity and errors rates by offline training	Integrating deep learning with model - driven structure for close to optimal performance at intermediate complexity	May generalize poorly across varying channel conditions , depends on training data
[3]	Survey on massive MIMO antenna design on 5G with emphasis on the mutual coupling and the mitigation strategies.	Massive MIMO helps to increase efficiency and capacity , while mutual coupling impairs antenna performance	Comprehensive overview for antenna challenges and coupling reduction methods to improve performance	Survey work without practical implementation or experimental validation
[21]	Introduces a data-driven DL detector (AMIC-Net) by unfolding accelerated MIC with sparse connections and trainable parameters	AMIC-Net approximates to OAMP-Net accuracy with reduced complexity and higher performance, particularly on the high-order QAM.	high-performance hybrid deep learning model based design with softs activation to improve performance of high order modulation	Depends on multi-layer optimization and training data , growing training complexity
[22]	This paper presents a survey analyzing of massive MIMO detection methods across algorithms, channel modeling, and performance parameters	Emphasizes on performance - complexity trade -off in detection methods based on system configurations , SNR and BER	Presents a systematic comparison and performance evaluation of many detection algorithms within diverse condition	Relies on heterogeneous assumptions from prior studies and does not suggested novel method
[23]	Suggests hybrid massive MIMO detector in the combination of ZF/V-BLAST and matrix inversion approximation algorithms, stair matrix initialization and MMNet using deep learning	MMNet Has less complexity , better performance and enhances noise mitigation and detection accuracy .	Combines deep learning approaches , model-based , approximation with validation on realistic channel	Approximation accuracy is necessary in performance, and needs parameter tuning with dynamic channels.
[24]	Suggests Model-driven DL receiver which uses CNN-based channel estimation and SD-NN for MIMO-OFDM detection	Enhanced robustness and detection performance with low complexity over data - driven deep learning	Highly efficient hybrid (model + DL) system with strong robustness is particularly with impaired hardware and complicated channel conditions.	May suffer from generalization issues across channels and need training data
[25]	Introduces a model-driven AMP-DNN through unfolding AMP with learnable parameters to optimized signal detection	Enhanced trade-off performance of BER-complexity with stable convergence and robust performance in correlated channels	Good generalization with minimal trainable parameters , fast convergence and Low complexity	Assumes limited scalability in large systems and perfect CSI; requires training data
[26]	Suggests an Approximate Diffusion Detection (ADD) scheme that transforms deterministic iterative detectors into stochastic sampling-based	Has better complexity performance trade-off and enhanced BER and can achieve similar performance to that of ML.	Efficient performance gain via sampling , SVD-free flexible integration	Sub optimal over ML and can add to longer run times due to multiple sampling

	detectors without usage of SVD			
[27]	Presents a NOMA-Massive MIMO adaptive fuzzy-powered and ADMM-based IND initialized through MMSE ,	Substantial BER reduction and performance improvement in various MIMO system size and modulations	Rapid convergence, better accuracy through MMSE initialization, and scalable through RCO	May degrade at high SNR or very large-scale MIMO and Sensitive to tuning parameter
[28]	Suggests a model-driven AI architecture that consists of three roadmaps :DL, LLM-based design and CSI models	AI enhancements channel estimation , detection and adaptability in THz UM-MIMO	Unified multi-AI framework with explicit research future direction	Is limited in Practical implementation and experimental validation with majority of contributions at a conceptual level.
[29]	Overview of ultra-massive MIMO methods in both beam and spatial domains with channel estimation , modeling, precoding and multiplexing	Beam domain processing with superior performance-complexity trade-off through channel sparsity utilization,	Extensive PHY level analysis with explicit evaluation between beam and spatial domain techniques	Limited analysis of new channel properties and no high-level practical implementations.
[8]	Suggests light weight FFNN deep learning detector evaluated on multiple MIMO settings with QAM/QPSK and Rayleigh channels	present low BER over conventional and deep learning methods with low complexity particular at moderate-high SNR	Efficient performance-complexity trade-off with high scalability and accuracy	Restricted validation on realistic channel conditions and ultra-massive MIMO
[30]	Suggests hybrid MIMO detectors combining MLD, MMSE and ZF with LSTM use in large-scale systems	Enhanced BER/PSD with less complexity and no matrix inversion,	Robust large-scale detection with Effective performance-complexity trade-off	Need high training resources and limited in real-time validation

3.1. SUMMERY FOR THE LIMITATION

1. The majority of studies depend on simulations, minimal real-time and device analysis research.
2. Using Realistic channel models cause poorer performance as compared to ideal channel models.
3. There is a low scalability to very large MIMO scales (64x 64, 128x 128, 256x 256).
4. Although the complexity has been reduced, the challenge of high training costs is still not addressed.
5. Pervasive belief in perfect or even close-to-perfect CSI.
6. Device flaws, including precision, digital adapters, moving parts, and educational noise, are typically overlooked.
7. The research on THz and UM-MIMO is mainly theoretical rather than practical.
8. Lack of concern on latency and energy consumption.
9. Deeper integration of physical models is necessary for deep learning
10. There is no standard of accurate comparisons among the detectors

4. MASSIVE MIMO SYSTEM STRUCTURE

A general system architecture of a Massive MIMO system is first given, with a Systematic analysis of the current Massive MIMO techniques of detection and system architecture .

4.1. THE SYSTEM MODEL

let us consider a Massive MIMO system with a base station employing N_r antennas serving N_t single-antenna consumers, where $N_t \leq N_r$. Assuming a channel that is frequency-flat, the channel between N_t transmitted antennas and N_r received antennas are represented by a matrix $\widetilde{H} \in C^{N_r \times N_t}$ where

$\widetilde{H}_{ij}$ represents the channel between the $j-th$ send antenna to the $i-th$ received antenna. The $N_t$users send their signals one by one, generating a symbol vector $\tilde{X} \in C^{N_t}$. Each symbol belongs to a constellation $\widetilde{H}$. The received vector $\tilde{y} \in C^{N_r}$ is created when the transmitted signal vector propagates over the channel $\widetilde{H}$ and is contaminated by additive noise $\tilde{n}$. The correlation is as below [1, 6]:

$$\tilde{y} = \widetilde{H}\,\tilde{x} + \tilde{n} \qquad (1)$$

we choose an analogous real-valued representation, consideration the real $\Re(.)$ and imaginary $\Im(.)$ parts. Let $x = [\Re(\tilde{x})^T, \Im(\tilde{x})^T]^T \in R^K$, $y = [\Re(\tilde{y})^T, \Im(\tilde{y})^T]^T \in R^N$,$n = [\Re(\tilde{n})^T, \Im(\tilde{n})^T]^T \in R^N$, and

$$H = \begin{bmatrix} \Re(\widetilde{H}) & -\Im(\widetilde{H}) \\ \Im(\widetilde{H}) & \Re(\widetilde{H}) \end{bmatrix} \in R^{N\times K} \qquad (2)$$

Such that $K = 2N_t$ and $N = 2N_r$, this allows the system to be expressed in real-valued form in the following form:

$$y = H\,x + n \qquad (3)$$

Moreover, all elements in H and n have probability distributions of $CN\,(0,1)$ and $CN\,(0,\frac{N_t}{\rho})$, respectively. Therefore, the antenna means SNR of each receive antenna is $\frac{\rho}{N_t}$ It is further presumed that $E[xx^H] = \frac{\rho}{N_t}I$, where I is the identity matrix. At the receiver, an approximation of the broadcast vector x is derived using perfect knowledge of the channel state, H, the set of symbol x, and the observation y. Massive MIMO detectors compute the transmitted vector x in a real-valued constellation x^k with the help of the received signal vector y and channel matrix H. The channel matrix is usually supposed to be known at the receiver and unknown at the transmitter. The massive MIMO detection problem becomes one that should solve the discrete optimization problem:

$$\hat{x} = arg\,min_{x\in x^k}||y - Hx||^2 \qquad (4)$$

This is NP-hard because of the finite constellation limitation. The ML detector is a perfect algorithm to use when encountering the MIMO detecting problem, as it performs a comprehensive scan of the possible constellation symbols. nevertheless, the ML detector's computational complexity increases at an exponential rate with the amount of sent data sequences, making it unsuitable for massive MIMO applications [6].

The problem with massive MIMO is that as the antennas number increases, the computational complexity will increase, making the signal processing process complicated and the process of detecting signals coming from users tough and complex.

5. MASSIVE MIMO DETECTION

This section focuses on the most essential methods of detection in the Massive MIMO system

5.1. MF DETECTOR

MF treats interfering signal of the other data sub-streams as pure noise by setting A = H. The incoming signal under the MF estimation is:

$$\hat{x}_{MF} = S(H^H y) \qquad (5)$$

It operates efficiently when K is substantially less than N, but performs poorly relative to more complicated detectors. MF, also known as maximum ratio combining (MRC), seeks to enhance the SNR of each received stream while ignoring the effects of inter user interference. A square MIMO system's performance suffers greatly if the channel is not properly conditioned [13].

5.2.ML DETECTOR

Maximum likelihood (ML) has highest results. nevertheless, it does a thorough search to determine all viable solutions to the incoming signal. The ML algorithm can be mentioned as follows:

$$\hat{x}_{ML} = arg\,min_{x\in O^K} ||y - H||_2^2 \qquad (6)$$

The ML detector estimates the incoming signal $\hat{x}_{ML}$. The ML complexity -based detector increases exponentially with the number of antennas o^{N_t}. As a result, the ML method is inappropriate for real word application because of the high complexity.[23]

5.3. LINEAR ZF DETECTOR

The ZF detectors is more efficient compared to MF detector. It attempts to highest the incoming SINR (signal-to-interference-plus-noise ratio) through the inversion of the channel matrix. The linear ZF detector equalizer matrix is given below:

$$A_{ZF}^H = (H^H H)^{-1} H^H = H^+ \qquad (7)$$

H^+ denotes the pseudo-inverse of the matrix H. It is essential to note that the ZF detector disregards noise and work well in the case of low interference [23].

5.4. LINEAR MMSE DETECTOR

Minimum mean-square (MMSE) estimate is the other linear detector methods which take in to consideration the impact of noise. Therefore, It achieves better performance than the MF and ZF linear detector at low SNR. The algorithm reduce the mean-square error between the transmitted signal (x) and $H^H y$, as shown below:

$$A_{MMSE}^H = arg\,min_{H\in^{Nr\times Nt}} E||x - H^H y||^2 \qquad (8)$$

The MMSE detector considers the effect of noise can be defined as:

$$A_{MMSE}^H = (H^H H + \sigma^2 I)^{-1} H^H \qquad (9)$$

The MMSE is computationally complex as it depends on high-order matrix inversion. Furthermore, high order matrices are unstable with regard to the algorithm performance. Furthermore, the MMSE based detector is quite ineffective in operation with ill normalized channels [5,23].

6. FUNDAMENTAL OF DEEP LEARNING ARCHITECTURES IN WIRELESS COMMUNICATION SYSTEM

Since 2017, deep learning has become an effective tool in wireless communications systems due to its capability to represent complex non-linear relationships. In particular, many neural network architectures have been widely adopted as basic models for signal processing tasks. Deep learning approaches are mainly used to address three main problems in large-scale antenna systems: computational difficulty , modelling difficulty, and measurement difficulty. This section briefly presents the basic architectures, which are the (DNN) deep neural network , the Recurrent Neural Network (RNN) and the convolutional neural network (CNN). It forms the basis of modern detection techniques based on deep learning for MIMO systems

6.1. DEEP NURAL NETWORK (DNN)

The simplest form of DNN is MLP Multilayer Perceptron. It consists of feed forward fully connected layers, in which each neuron is fully connected to all neurons in the next layer. The activation function of every neuron in an MLP is nonlinear and therefore the network can identify complex structure in a tabular data set. In Figure 1, the MLP model is represented by a basic structure with a one input layer, a one hidden layer and a one output layer. In the input layer, each node (such as feature 1, feature 2, feature 3) represents a component of the input feature vector. In the framework of massive MIMO detection , these features may correspond to channel coefficients ,received signal symbols, or a combination of both . The hidden layer performs a nonlinear transformation of the input data. Where each neuron in the hidden layer is connected to all neurons in the input layer, as shown by the dense connections in the figure. Each transformation is followed by a nonlinear activation function such as RELU or sigmoid. This nonlinearity enables the network to accommodate complex relationships between input features. The output layer takes the transformed features from the hidden layer and generates the final prediction .Due to their design simplicity, MLPs can be used in the real world where they need only minimum computing power. To identify intrusion in WSNs, where edge nodes are less competent in computation, the researchers demonstrated that MLP was more accurately classified in comparison to the state-of-the-art method when acting with changed nonlinear enormous data on a real-time basis. A model driven by MLP was used to tackle the problem of localization in the internet of everything (IoE) [4].

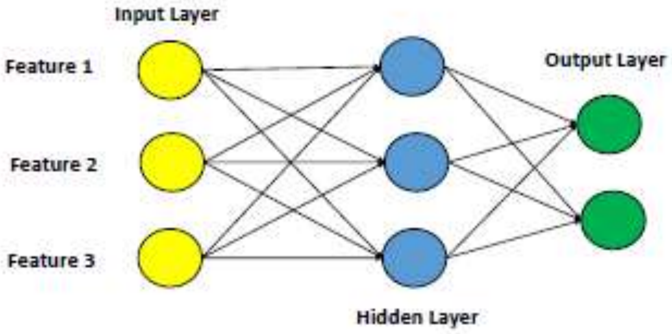

Fig. 1. Architecture of a MLP [4]

6.2. CONVOLUTIONAL NEURAL NETWORK (CNN)

Figure 2 display the architecture of a simple CNN, which comprises an input layer, multiple convolutional and pooling layers, followed by a fully connected layer and an output layer. The feature maps of a CNN architecture are formed by the convolutional layers, using filters or kernels the down sampling of feature maps is done by the pooling layers to reduce their spatial dimension. Following convolutional and pooling layers, fully connected layers are employed for high-level reasoning. In the input stage, the data is expressed in a structured form (such as a two-dimensional array). In the framework of massive MIMO systems, this input may represent the received signal matrix or channel matrix, where there is a spatial relationship between the subcarriers and the antennas. Convolution layers apply a set of trainable filters (kernels) to local regions of the input. Each filter slides through the input matrix and performs a convolution operation to produce feature maps. This process captures local spatial patterns and correlations. Using joint weights substantially reduces the number of parameters relative to fully connected networks. After convolution, pooling layers are utilized to reduce the size of feature maps. This reduces computational cost and spatial dimensions while preserving the most prominent features. Typical pooling operations include max pooling and average pooling. Pooling also enhances the network's robustness to noise and small variations in input. The extracted features are then passed to fully connected layers, where high-level inference is performed and these layers combine the learned features to generate the final output. In detection applications in MIMO systems, the output layer usually represents the estimated transmitted symbols. Although CNNs are mostly utilized in video and image processing due to their capacity to acquire finer details of patterns based on grid-like information, hey find a wide application in the wireless communication industry. In [4] CNN-IR, a smart receiver, is presented that uses a CNN to reduce errors of data recovery caused by channel distortions such as noise or multipath fading. It substitutes standard equalization and channel estimation approaches with a learned CNN that understands the intricate interaction between sending and receiving signals. CNNs were employed for, spectrum sensing, channel estimation and interference identification [4].

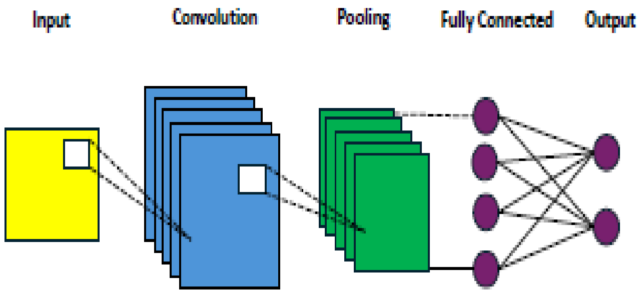

Fig. 2. Architecture of a Convolutional Neural Network [4]

6.3. RECURRENT NEURAL NETWORK (RNN)

It is fundamental to keep track of the previous input state in sequential data tasks such as time series analysis and natural ,language processing, and other tasks that involving temporal dependencies. However, feed-forward neural networks such as MLP and CNN, in which data travels uni directionally from single layer to the next, lack this ability to recall the previous state's input. In an RNN, the preceding step's output is used as input. Figure 3. shows the unfolded structure of a Recurrent Neural Network (RNN), which is designed to model sequential and time-varying data.Unlike feed-forward neural networks, recurrent neural networks incorporate a feedback mechanism that allows information to persist across time steps through a hidden state. On the left side of the figure the short representation shows a single recurrent unit. where the input x and the previous hidden state h are combined to produce the output y and the updated hidden state. Looping refers to reusing the same unit over time. While the right side shows how the network is unfolded over multiple time steps $t-1$,t and $t+1$ revealing the temporal dynamics of the model. At every time step t, the hidden state h_t is calculated based on the previous hidden state $h_t - 1$ and the current input x_t. The output $y_t$is then generated from the hidden state. One major advantage of RNN is that they share the same parameters across all time steps, which decreases the number of trainable parameters and enables the network to generalize across sequences of varying length.

The hidden state acts as a memory that captures the temporal dependencies in the input sequence. One of the primary distinctions between feed-forward neural networks and RNNs is that the former lacks a looping node. It can represent an RNN as functionf_θ of type:

$$(x_t, h_t) \rightarrow (y_t, h_{t+1}) \qquad (10)$$

Where x_t , h_t, y_t denote the input, hidden state, and output vectors, respectively and θ is a neural network parameters. [4].

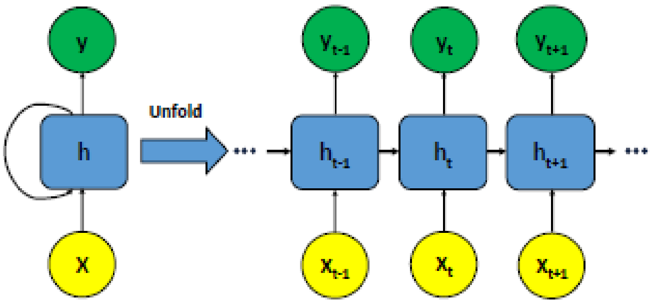

Fig. 3. Basic Recurrent Neural Network [4]

The structures referred to above constitute the basic building blocks of modern MIMO detectors based on deep learning. In the next section, these structures are adapted and integrated into advanced detection frameworks to reduce computational complexity and enhanced performance in Massive MIMO systems.

7. DEEP LEARNING BASED DETECTION FOR MASSIVE MIMO SYSTEMS

Building on the basic architectures presented in Section 6, this section focuses on massive MIMO systems detection techniques based deep learning as these approaches aim to overcome the drawbacks of conventional detectors by improving the trade-off between detection performance and computational complexity.

Generally deep learning - based MIMO detectors can be classified in to three categories . Figure 4 presents a classification of detection techniques in massive MIMO systems, classifying them into conventional methods and others based on deep learning. The deep learning-based methods are in turn divided into hybrid techniques ,data-driven techniques and model-driven techniques based on their design principles.

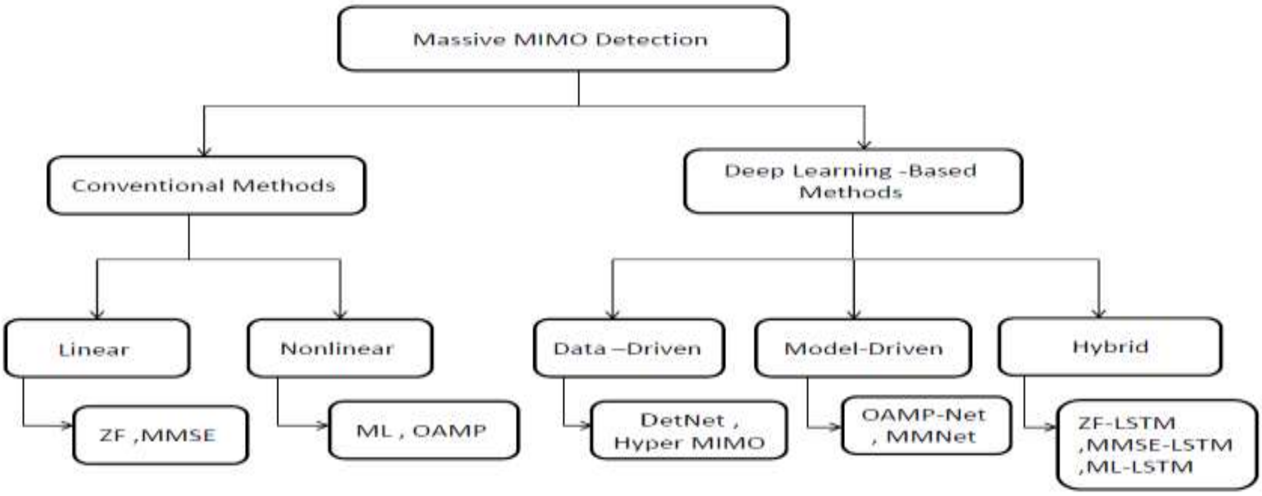

Fig. 4. Classification of massive MIMO detection techniques

As shown in Figure 4, conventional detection methods are divided into linear and non-linear approaches while deep learning-based methods are classified according to how domain knowledge is integrated into the learning process. This classification provides a clear framework for analyzing and comparing different detection techniques

7.1. MODEL-DRIVEN DETECTORS

As shown in fig 4, model-driven approaches integrate expert knowledge from traditional signal processing algorithms in deep learning architectures which enhanced efficiency and interpret ability.

7.1.1. OAMP-NET

A model-driven deep learning network is illustrated using the (OAMP-Net) orthogonal approximate message passing network. The OAMP-Net detection algorithm extends the existing OAMP method by adding certain customizable parameters, however a tight assumption is required. In every layer of the OAMP-Net, the matrix inverse takes precedence. As a result of its enormous computational complexity, it is unsuitable for practical implementation. This algorithm has several advantage and disadvantage , such as It outperforms DetNet in terms of (SER) symbol Error Rate Under independent and identically distributed i.i.d Gaussian channel conditions, OAMP-Net mitigates the large trainable-parameter count typical of other deep learning methods. OAMP-Net employs only two learnable parameters in every layer and performs effectively when employing lower-order modulation schemes. Nonetheless, the matrix inversion required at every layer lead to high computational burden. Furthermore, its performance deteriorates over realistic and correlated channels. It also adopts a single detector for various channel models and performs unsatisfactorily in massive MIMO scenarios [23].

7.1.2. MMNET

MMNet is a deep learning-based architecture for massive MIMO detection with a flexible channel instances architecture. The MMNet improves on the OAMP-Net and DetNet poor performance in real channel models. The MMNet structures strikes a balance between complexity and flexibility in each network layer. prior DL detected approaches, such as OAMP-Net and DetNet, were trained offline and used Architecture tailored to a single realization of the channel nevertheless, the MMNet is developed using several channel realizations and allows for online as well as offline training. The massive MIMO model represented in (11) generates training and testing data for the MMNet, with randomness coming from the channel matrix (H),the signal (x) and the noise (n).

$$y = H\,x + \,n \qquad (11)$$

this type has a several advantages and disadvantages such as it mitigates the system performance degradation of OAMPNet and DetNet under realistic channel conditions, it supports per-realization online training for H and does avoids matrix inversion at each layer. It achieves low computational complexity than Det-Net and OAMPNet architectures. It delivers superior performance compared with Det-Net ,MMSE, and OAMPNet in realistic channels across the linear and denoising stages of each layer, it strikes a balance trade-off between complexity and flexibility. during each layer's linear and denoising stages**.** When utilizing high-order modulation methods, performance suffers. The deep neural network must be maintained for every channel matrix (H) realization, complicating real-world implementation. Latency occurs as a result of sequential online training [23].

7.2. DATA-DRIVEN METHODS

According to the classification shown in figure 4 , data-driven methods rely entirely on training data to learn the relationship between transmitted symbols and received signals learn the detection process directly from data without relying on explicit mathematical models

7.2.1. DETNET

DetNet employs a deep neural network designed for massive MIMO detection, which employs a projected gradient descent algorithm by convert this algorithm in to a layerd neural network structure. DetNet works applicable in low-order modulation and simple channel setting techniques. A modified DetNet needs only a few model parameters to be tuned; nonetheless, DetNet training is non-stable in the case of coupled and realistic channels. Furthermore, the DetNet model has a poor scalability because of the high number of training parameters. This type offers several advantages and downsides, including acceptable performance when evaluated on constant and Rayleigh fading channels. It demonstrates strong performance under low-order modulation schemes such as BPSK and 4 - QAM. It has a huge number of learnable parameters, hereby making them impractical for high-order modulation formats and massive MIMO systems. It applies a one detection model to various channel characterization. Realistic and linked channels do not have stable performance [23].

7.2.2. HYPER MIMO

A Hyper MIMO-based detector replaces the MMNet training procedure with a one inference across a learned hyper-network, which reduces the amount of MMNet variables. In comparison to MMNet, Hyper MIMO performs marginally worse. It must also be retrained when significant variations in channel statistics are observed. This kind has several advantages and disadvantages, including reduced complexity compared to MMNet. This is accomplished by reducing the number of learnable parameters count in every layer., It outperforms the OAMP-Net model, was actually applied, and has strong resilience to user movement. It has lesser performance than the MMNet algorithm and must be maintained when the channel matrix changes significantly [23].

7.3. HYBRID DETECTORS

As illustrated in Figure 4, hybrid methods integrates deep learning models with conventional detection algorithms to take advantage of the strengths of both models

7.3.1. ZFE-LSTM

ZFE-LSTM equalizers alter detecting signal in MIMO systems using the capacity of LSTM (Long Short-Term Memory) networks for long-term memory retention and sequential data processing. The major emphasis of typical ZF equalizers is to eliminate inter symbol interference via channel matrix inversion. nevertheless, this method is extremely sensitive to amplification of noise, particularly when the channel matrix exhibits poor conditioning. The suggested technique effectively reduces multiuser interference and improves detection accuracy under retaining reasonable complexity. This restriction is addressed by LSTM-based equalizers, which use machine learning methods to predict the temporal correlations and nonlinearities of MIMO channels. By learning on various channel circumstances, LSTM networks understand the channel's statistical features, allowing for stable equalization even in difficult settings like as heavy deep fading or noise. This adaptive feature improves detection performance, resulting in considerable improvements in system performance metrics like BER [30].

7.3.2. MMSE-LSTM

The integration of LSTM networks and MMSE equalization for detecting signal in massive MIMO systems leverages the benefits of each of the two technologies to boost efficiency. MMSE equalization reduces the impacts of noise an inter-symbol interference (ISI) through minimization the mean square error between sending and receiving signals, allowing for a preliminary approximation of delivered data. nevertheless, MMSE frequently suffers with challenging channel conditions and nonlinearities [5]. The LSTM deep network enhanced the MMSE output through residual errors learning and mitigating with respect to limitations such as channel nonlinearities and hardware non-idealities through its ability to represent sequential relationships and model temporal correlations. The hybrid technique thus achieves better performance than traditional MMSE by leveraging the deep learning methods to extracting non-linear features and adapt with Time-varying wireless channel fluctuations, that are common in massive MIMO settings. The main benefits comprise lower BER, increased robustness to interference and fading, and tolerance to nonlinear aberrations in comparison with standalone MMSE the MMSE-LSTM combination improves detector reliability and accuracy, especially in contexts dense user environments under challenging propagation conditions [30].

7.3.3. MLD-LSTM

Maximum Likelihood Detector (MLD) integrating long short-term memory networks it integrates the benefits of traditional estimation techniques combined with deep learning to improve detecting signal of MIMO systems. It reduces mistakes caused by the detecting process, hence the MLD approach comprehensively looks for a transmit signal vector, by optimizing the conditional likelihood of the received signal provided the channel matrix. on the other hand its computational complexity increases grow exponentially with increasing modulation order and antenna number , rendering it unsuitable for massive MIMO systems. The use of LSTM networks mitigates these constraints by estimating the detecting process with a learnt system. LSTMs are very good at detecting spatial and temporal correlations in temporal data, enabling them to correct errors and learn residual patterns in MLD estimations. Training the LSTM based on noise patterns and channel parameters further refines the MLD outputs, increasing detection reliability while keeping computational complexity small. MLD-LSTM better performance regular MLD in dynamic, noisy situations. It adjusts to real-world channel flaws such as interference and fading, which classical MLD does not directly address without incurring significant computational expense. Furthermore, it considerably lowers the search space, which minimizes latency and allows the system to work in real time [30].

It is clear from the previous discussion that data- driven methods provide high detection accuracy but require huge training data, while model-driven methods provide better interpret ability and lower complexity, while hybrid methods combine both advantages, making them suitable for practical massive MIMO systems.

Despite these developments, challenges such as training complexity and generalize ability and scalability to real-world channels remain open research issues

8. COMPARISON BETWEEN MASSIVE MIMO DETECTION AND MASSIVE MIMO DETECTION-BASED DL:

This section examines rigorous comparison between deep learning based detection methods and conventional detection methods in Massive MIMO systems with respect to computational complexity, practical feasibility and BER performance in [12],[23],[30].it is apparent that deep learning detector achieve a better performance with reduce runtime complexity making them more suitable for large-scale MIMO systems.

Table 2. Comparison between conventional massive MIMO detection and deep learning-based massive MIMO detection

	Massive MIMO detection	**Massive MIMO detection-based DL**
Detection Principle	- Model-based using linear/nonlinear signal processing - It is based on precise mathematical empiricism of the channel. - It uses conventional detection algorithms such as ZF, MMSE, etc. - Its performance is closely related to CSI accuracy and channel premises.	- It is built on the neural network model (DNN, CNN, LSTM, etc.). - Becomes acquainted with the detecting process with the help of data. - It is characterized by the ability to represent nonlinear and complex interactions in the channel.
BER Performance	- Moderate BER in small and midsize systems. - It works poorly when the number of antennas increase and high order modulations (16QAM, 64QAM	- Has BER less than conventional detectors (e.g ZF,MMSE,...etc) at medium and high SNR and is more appropriate in large scale MIMO.
BER vs SNR	- Requires high SNR value to achieve low BER performance for example in 256×256 MIMO system the MMSE detector requires SNR=9dB to achieve BER =10^{-3}.[30]	- Requires lower SNR value to achieve low BER performance for example in 256×256 MIMO system the MMSE-LSTM detector requires SNR=5dB to achieve BER =10^{-3} . [30]
Computational Complexity	- The computational complexity increases exponentially when the number of antenna increases ,MMSE detector has cubic complexity due to matrices inversion which is not practical when the number of antenna increasing, ZF has computational complexity equal to ZF(O($N_r N_t^2$)) , the computational complexity of the ML detector grows exponentially with the number of decision variables (O^k) .[23]	- Detectors based on deep learning are trained to predict with constant number of forward passes through the network and this leads to predict ability and low computing complexity. Deep learning methods that are model-driven are less complex, as only a limited number of parameters are learned for example MMNet O(bN_r^2L), OAMP-Net (ON^3) .[12]

Convergence / Iterations	- Iterative methods (AMP/OAMP) involve number of iterations such as (10-20) iterations	- faster convergence because it has fixed number of layers (L)
Scalability (Large MIMO)	- Restricted scalability due to performance/complexity trade-off	- Due to parallel processing it has highly scalability
Robustness and Imperfect CSI	- Highly sensitive to channel estimate errors and correlated channels	- More resilient to imperfect CSI and channel variations.
Training Requirement	- This does not need any training; it is detected by doing some analytical computations using the modeled expectation of the channel.	- Training dataset required; this can be re-trained with any change in system properties such as modulation order, SNR range or antenna design.
Real-Time Feasibility	- Due to matrix inversion cost it is limited for large systems	- High due to fast inference after training
Flexibility	- static mathematical models	- Adaptive to channel conditions ,modulation and SNR

9. LIMITATIONS AND CHALLENGES ASSOCIATED WITH DEEP LEARNING-BASED MASSIVE MIMO DETECTION

This section highlights a most significant challenges to the detecting process in Massive MIMO systems in the context of deep learning. Despite the benefits based deep learning in Massive MIMO systems, there are certain considerations. Machine learning models, especially deep learning models, often require a large amount of labelled training data.When utilizing machine learning to detect MIMO systems, the availability of classified MIMO datasets is an important consideration. Deploying and training a deep learning model may be resource-intensive, especially for massive MIMO systems. Effective training approaches and adequate processing power may be required [31]. The massive MIMO detection using deep learning is susceptible to various challenges, such as low generalization to various channel conditions and SNR, extensive training and computation needs, susceptibility to inaccurate matches when training and deployed to different conditions, large antenna system challenges, and implementation challenges in real time. These limitations hinder the practical applicability of deep learning-based detectors in large-scale MIMO systems.

9. CONCLUSION

Massive MIMO technology is projected to improve the user experience and generate new revenues through novel mobile services. As a result, massive MIMO will continue to be a formidable competitor in both developed and emerging markets over the next decade.In this work, we present an overview of the multiple detection methods for Massive MIMO systems, the most important deep learning networks used in the detecting signal process in Massive MIMO systems, as well as the most significant challenges to the deep learning applications in Massive MIMO systems.

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