International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7220
***Article Received**: 30 April 2023 **Revised:** 18 June 2023 **Accepted:** 29 June 2023*

On Investigations of Machine Learning and Deep Learning Techniques for MIMO Detection

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Abstract—This paper reviews in detail the various types of multiple input multiple output (MIMO) detector algorithms. The current MIMO detectors are not suitable for massive MIMO (mMIMO) scenarios where there are a large number of antennas. Their performance degrades with the increase in number of antennas in the MIMO system. For combatting the issues, machine learning (ML) and deep learning (DL) based detection algorithms are being researched and developed. An extensive survey of these detectors is provided in this paper, alongwith their advantages and challenges. The issues discussed have to be resolved before using them for final deployment.

Keywords-ML; DL; AI; MIMO detection; mMIMO.

I. INTRODUCTION

The core problem of any type of communication is to accurately or nearly reproduce a message transmitted from one location to another [1]. In wireless communication networks, Multiple Input Multiple Output (MIMO) antenna technology has considerably improved data speeds, dependability, and overall performance. The advantages offered by MIMO systems, have revolutionized wireless communication and are now an essential part of any modern wireless network. Multiple data streams may be sent at once over the same frequency range thanks to MIMO. The capacity of wireless networks may be efficiently increased using MIMO systems, which employ multiple antennas at the transmitter and receiver. More users may be served within a given bandwidth owing to increased data rates and improved spectral efficiency made possible due to this [2].

Multiple data streams may be sent at once over the same frequency range thanks to MIMO. The capacity of wireless networks may be efficiently increased using MIMO systems, which employ multiple antennas at the transmitter and receiver. More users may be served within a given bandwidth owing to increased data rates and improved spectral efficiency made possible due to this [3]. Wireless networks can have better coverage and a longer range thanks to MIMO technologies.

MIMO may concentrate energy in certain directions by utilizing spatial multiplexing and beamforming methods, enabling messages to travel further distances and scale barriers more successfully. This is especially advantageous in urban and interior situations, where signal attenuation and obstruction are frequent problems. In busy wireless scenarios, MIMO can reduce interference. MIMO systems may recognize and divide signals from multiple sources, even when they share the same frequency ranges, by taking advantage of spatial dimension. This enhances the overall quality of service and allows for a more harmonious union of various wireless networks.

Wi-Fi, LTE, and 5G are just a few of the wireless communication technologies that MIMO technology is compatible with [4]. It is a flexible and scalable approach for enhancing wireless networks since current equipment may be upgraded using firmware or software. MIMO is still a crucial component of higher-capacity and more dependable communication networks as wireless technologies develop.

In MIMO wireless communication, despite the several added advantages, a big obstacle is the subpar performance of detection techniques resulting from the trade-off between computational complexity and error rate performance [5]. The computational complexity is extraordinarily high while performance is at its best, and vice versa. In this research paper, a survey of various advances in AI for effective MIMO detection is done. The organization of the rest of the paper is described as follows. In the next section, the applications of different types of artificial intelligence (AI) techniques in

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wireless communication are discussed which is followed by discussion on the importance of implementation of a good MIMO detection system in the following section. Then in the next section, the usage of metaheuristics for MIMO detection is discussed. In the upcoming section, a survey on MIMO detection using AI techniques is discussed in detail which is followed by the concluding remarks.

II. AI FOR WIRELESS COMMUNICATION

For finding solutions to complex problems in wireless communications, AI techniques such as machine learning (ML) and deep learning (DL) are replacing the conventionally used metaheuristics and classical optimization approaches. Better accuracy, automatic feature extraction, scalability, ability to handle large amounts of data that is changing (evolving), need for lesser human intervention, improved decision making and fewer chances of falling into local optimum are few of the many advantages offered by DL and ML techniques.A novel type of artificial neural networks (ANNs) forms the foundation of deep learning (DL) which are known as Deep Neural Networks (DNNs) [6]. Reinforcement Learning (RL) is also emerging as a solution to solve many issues and challenges in existing MIMO systems [7-8]. These technologies have provided numerous solutions for various MIMO communication issues, including resource allocation, positioning, sensing, and localization, as well as signal detection, classification, and compression. AI-enabled MIMO communication is the best tool for giving wireless systems the adaptability, wisdom, and productivity required to manage the limited radio resource effectively and provide consumers with the highest level of service. Various supervised and unsupervised learning techniques are used for solving complex challenges in MIMO wireless communication systems.

Federated learning (FL) is also being used for MIMO wireless communication system's performance enhancement [9]. By training AI models without allowing anyone else to see or access the data, federated learning offers a method for releasing data to power new AI applications. It is a distributed DL method. FL is applied to wireless communication for channel estimation, symbol detection, vehicular networks (V2X), network slicing, the internet of things, computational offloading at the edge, etc [10]. In [11], a new scheme for cell-free massive MIMO (CFmMIMO) is proposed for networks to support any FL framework.

In [12], FL's deployment is investigated in an energy-harvesting mMIMO wireless system for serving different user equipment which is fueled by independent energy-harvesting sources. In [13], FL is used for the estimation of CSI for both simple and reflective intelligent surface (RIS) aided mMIMO systems. A lot of research work has been done for the improvement of the performance of MIMO systems in wireless communications using ML and DL which is briefly described in Figure 1.

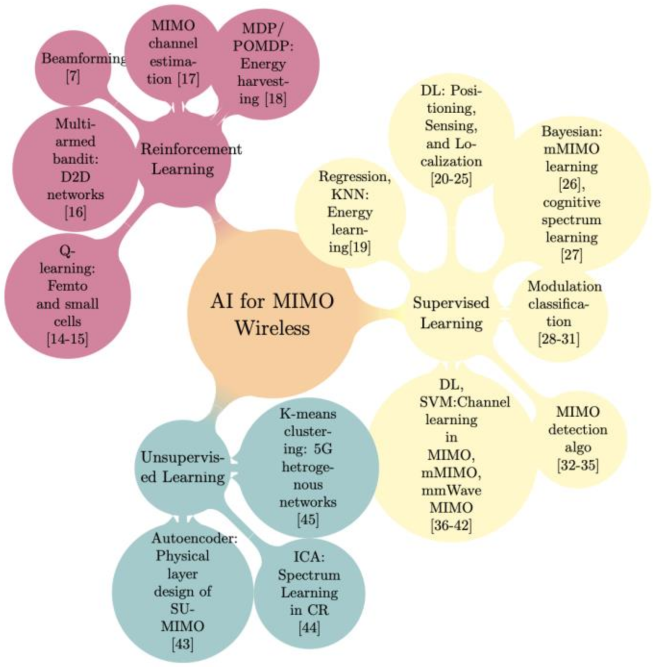

Figure 1. Survey Roadmap of Applications of AI in Performance Enhancement of MIMO Wireless Communication Systems

III. THE PROBLEM OF MIMO DETECTION

A. *Importance of an Efficient MIMO Detection Algorithm*

Multiple antennas are utilized at the transmitter and receiver in a MIMO system to establish numerous signal channels between the two components. As a result, the system performs the transmission and reception of numerous streams of data concurrently over the same frequency range. Channel estimation and signal detection are the two fundamental processes in the MIMO detection process, which are described as follows:

(i.) Channel Estimation: Estimating the channel between the transmitter and receiver is the initial stage in MIMO detection. To do this, known pilot symbols are transmitted from each transmitting antenna which is measured by receiving antennas. These observations are used by the receiver to calculate the channel coefficients between each set of antennas.

(ii.) Signal Detection: The receiver uses the received signals and the estimated channel coefficients to identify the broadcast symbols after the channel has been estimated. In MIMO systems, a number of signal detection methods are available, such as Maximum Likelihood (ML), Zero-Forcing (ZF), and Minimum Mean Square Error (MMSE).

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Thus, MIMO detection is a challenging procedure that starts with calculating the transmitter-receiver's channel before utilizing a variety of signal detection [46].

B. Optimal MIMO Receiver

Data detection from noisy measurements of the sent signals is a challenge in the design of MIMO receivers for wireless communication systems. Every practical circumstance inevitably results in the receiver making sporadic mistakes because of the noise. Consequently, from both a theoretical and practical standpoint, it is appealing to build a receiver that has the quality that this likelihood of error is modest. For MIMO signal detection, Maximum Likelihood (ML) and Maximum A Posteriori Probability (MAP) Detectors are the ideal or optimal receivers.

In ML detection, the receiver evaluates all potential symbol combinations in order to identify the most likely sent symbols. Though computationally expensive, this method offers the best error rate performance. The vector that minimizes the Euclidean distance between the received vector and all potential combinations of the sent symbol vectors is the one that ML detection produces, as given in equation 1. Here, y denotes the received symbol, x is the transmitted symbol, H is the channel matrix, and $\hat{x}$ is the estimated symbol.

$$\hat{x} = argmin_x ||\, y - Hx||^2 \qquad (1)$$

In order to maximize the probability function as stated in equation 2, the ideal symbol vector for ML detection must be identified [47].

$$\hat{x} = argmax_{x \in X^{NT}}\, f(y|x) \qquad (2)$$

Here, f(y | x) denotes the likelihood function for x for the given received vector y and NT stands for the number of transmitting antennas. It is well known that the ML detection problem is NP-hard. This indicates that no existing algorithms for solving the problem under consideration are polynomially complicated in the number of symbols jointly identified unless there is some additional underlying structure. For this reason, many suboptimal receivers that are computationally simpler have been considered in the literature. The MAP detector is an additional ideal detector that estimates the transmitted symbols using the prior knowledge of the transmitted symbol vector x and the received signal vector y [48]. The likelihood function and prior probability of the sent symbols are both taken into account by the MAP detector while estimating the transmitted symbols. In low SNR scenarios, this method outperforms the ML detector, but it is computationally complex. Due to their lower complexity and effective performance, suboptimal detection approaches like Minimum Mean Square Error (MMSE) and Zero-Forcing (ZF) detection are utilized in practice [49].

C. Sub-optimal MIMO Receiver

Various other types of sub optimal MIMO detectors are also used which are discussed in this section. The first category is linear sub-optimal MIMO detectors such as ZF, MMSE, and matched filter (MF). The advantage of this type of MIMO detector is that these are computationally efficient for small-scale MIMO systems and provide good performance. However, the disadvantage is that these involve a matrix inversion of O(N cube) complexity and thus offer limited performance for massive MIMO.

In ZF detection, the channel effects are eliminated by multiplying the received signals by the inverse of the channel matrix. The transmitted symbols are then recovered by demodulating the resulting signal. This approach makes the assumption that the channel matrix is invertible and that the system is noise-free. In reality, the channel matrix might not be invertible and the system is almost always noisy. ZF detection experiences signal distortion and noise amplification despite how straightforward it is. To balance computational complexity and performance in MMSE detection, the receiver applies a weighted sum of the ZF and ML detection techniques. The second category is linear iterative sub optimal MIMO receivers include Gauss Seidal (GS), Conjugate Gradient (CG), Successive Over Relaxation (SOR), Jacobi, etc. The main advantage of these types of MIMO receivers is that there is no need for performing the computationally expensive task of matrix inversion and thus only a complexity of O(N square) makes them implementation-friendly. The disadvantage, however, is that their performance is bounded by minimum mean square error (MMSE).

Interference cancellation (IC) is another category of non-linear sub-optimal MIMO detectors . These are of two types i.e., successive interference cancellation (SIC) and parallel interference cancellation (PIC). The benefit of using these is that error correction coding is integrated into the multi-user detection (MUD) process. However, their disadvantage is that these add higher complexity to the system [50-51].

Tree search-based non-linear sub-optimal MIMO receivers are of two types i.e., depth-first based and breadth-first based. Their advantage is reduced complexity as compared to optimal ones, with near-optimal performance. Their disadvantage is that there is a possibility of exponential worst-case computational complexity and it is thus impractical for massive MIMO systems [52].

The message parsing (MP) nonlinear sub-optimal MIMO receivers such as approximate MP (AMP), orthogonal AMP

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(OAMP), belief propagation (BP), and expectation propagation (EP) perform better as compared to MMSE with acceptable complexity. The AMP detector is implementation friendly, simple, and cheap and is used for many practical scenarios. However, the disadvantage of using these is that they suffer from convergence problems due to loopy factor graphs. AMP, being an iterative method, may diverge in problematic settings. It works fine for known channel distributions but not for complex channel environments such as the Saleh-Valenzuela channel. Another category is the sub-optimal semi-definite relaxation (SDR) MIMO detector which is more robust thaan AMP and has polynomial complexity [53]. However, it is much slower than AMP in practice. Thus, to overcome the issues of conventionally used sub-optimal MIMO detection algorithms, metaheuristic techniques as well as AI techniques are used which are described in the next two sections.

IV. MIMO DETECTION USING METAHEURISTICS

For MIMO detection, metaheuristic algorithms have been investigated, especially in cases when there are few transmit and receive antennas. Through effective exploration of the solution space, metaheuristics may be applied to enhance the detection process. The performance of several detection methods, such as maximum likelihood (ML) detection or sphere decoding, can be enhanced by combining metaheuristics with them. Metaheuristics are flexible enough to adapt to various MIMO system configurations, such as varied numbers of antennas, modulation types, and channel parameters. Some of the MIMO detection algorithms by the usage of metaheuristics are described in Table I.

TABLE I. RECENT ADVANCES ON MIMO DETECTION ALGORITHMS USING METAHEURISTICS

Sr. No.	Year	Authors	Ideas
1	2007	A. A. Khan, M. Naeem and S. I. Shah [54]	A Particle Swarm Optimization (PSO) based MIMO detection algorithm that provides almost near optimal BER performance and that too in lesser number of iterations is demonstrated.
2	2010	K. Khurshid, S. Irteza and A. A. Khan [55]	An Ant Colony Optimization (ACO) based MIMO system receiver detection algorithm for symbol detection in MIMO system is proposed.
3	2010	J.-K. Lain and J. Y. Chen [56]	A modified version ACO for MIMO detection is used which outperforms the older inefficient detection schemes such as the ML Detector as they need exhaustive search.
4	2014	J. C. Marinello and T. Abrão [57]	A combination of ACO with lattice reduction (LR) algorithm is done to obtain the LR-ACO based MIMO receiver which provides betterment in the performance and complexity tradeoff in MIMO systems' detection schemes at the receiver side.
5	2017	A. Datta and V. Bhatia [58]	A robust detection algorithm called modified gravitational search algorithm (MGSA) is proposed for MIMO detection which exploits the concept of the gravitational search algorithm for MIMO detection.
6	2019	A. Datta and V. Bhatia [59]	For large MIMO detection, a stochastic bio-inspired meta-heuristic method is put forth in this research. The bioluminescence of fireflies serves as the inspiration for the proposed method, which updates results in the search space using a probabilistic measure.
7	2021	B. Trotobas, Y. Akourim, A. Nafkha, et. al. [60]	The benefits of adding exploration to the traditional tree-based MIMO detectors are accomplished by the usage of a new interpretation of the bio-inspired detector based on the firefly algorithm (FA).

However, there are a few considerations. In comparison to certain machine learning techniques, metaheuristics may have a higher computational cost depending on the particular method utilized. For large-scale MIMO systems, this factor is very crucial.For metaheuristics to work at their best, parameters must frequently be manually adjusted. This tweaking procedure might take a while and calls for subject knowledge.

V. MIMO DETECTION USING AI

Deep learning techniques in particular have shown potential for MIMO detection problems. In MIMO systems, deep learning models like DNNs and convolutional neural networks (CNNs) can extract relevant features from the received signals and learn complicated mappings. They have the capacity to handle massive MIMO setups and achieve great detection accuracy. Deep learning models are well suited for MIMO detection as nonlinear mappings are frequently used in MIMO. Deep learning models can capture complex correlations between received signals and sent symbols. In MIMO channels, deep learning models can take use of the spatial and temporal correlations to enhance detection performance. The entire detection process may be made simpler by using end-to-end deep learning models that directly translate incoming signals to identified symbols [61]. Especially in massive MIMO systems, the conventionally used detectors don't show good performance and hence quite a lot of learning-based detectors are being developed. However, despite the advantages, there are a few considerations as well. Large quantities of labelled training data are often needed for machine learning models, especially deep learning models. When employing machine learning for MIMO detection, the accessibility of labelled MIMO datasets may be a

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factor. Deep learning model deployment and training can be computationally demanding, particularly for large-scale MIMO systems. It could be necessary to use effective training techniques and enough processing power.

The offline training stage of a DNN detector incorporates the majority of its computational complexity. A DNN detector, on the other hand, provides data detection during runtime with substantially reduced computing complexity. To do this, the operation may be completed in batches, which offers polynomial time complexity for data detection based on straightforward matrix additions and multiplications. These operations are far more straightforward than the computationally intensive matrix inversions/pseudo-inversions or searching methods used in traditional linear or nonlinear detection systems. Another important contrast between the two is that batch operations used in DNN designs are more suited to hardware implementation than hand-engineered methods. Some of the MIMO detectors based on AI are discussed in this section.

In [62], a model-driven DL network called as OAMPNet is proposed for MIMO detection. This network has good performance because it inherits the advantages of the Bayes-optimal signal recovery algorithm and deep learning methods. The network can be trained quickly and easily because there aren't many parameters that need to be optimised. Additionally, the time-varying channel may be handled by this network. However, there are a few cons to its performance as well.Though it outperforms the traditional OMAP MIMO detection algorithm, its performance is very poor as compared to the ML detectors. It is also suitable only for simple settings such as unitarily-invariant channels and since it uses matrix inversion operations, it is quite computationally expensive.

In [63], a twin-neural network based architecture is proposed for MIMO symbol detection and its performance is found to be quite close to that of the ML detector. A model-driven DL-based MIMO detection is accomplished by DetNet (Detection Network) [64]. For neural network ML detection, it was made utilizing the Projected Gradient Descent Method (or PGDM). It outperforms the more widely used expectation propagation-based MIMO detectors and iterative MIMO detectors like AMP, which are unable to operate at their best when faced with challenging circumstances and uncertain channel distribution. DetNet also beats MIMO detectors based on sphere decoding in terms of Symbol Error Rate (SER). Compared to Semi Definite Relaxation (SDR) MIMO detectors, it is more than 30 times faster and delivers higher accuracy. DetNet receives input in the form of signals that were received and accurate Channel Status Information (CSI). With a known channel distribution, it has shown to be reliable under challenging fixed channel conditions and varying channel cases. Due to DetNet's speed, real-time, near-optimal performance is feasible. It simply needs to train once in order to apply it to several models. Also, in the DetNet architecture, at each layer, there is an input of the weighted average of the outputs of all the previous layers, just like in ResNet. The limitations of DetNet are as follows.

Though it is better than LMMSE, it is more computationally expensive owing to its sophisticated structure. Training of DetNet is unstable for realistic channels. It is only suitable for simpler settings such as low-order modulation schemes, independent and identically distributed Gaussian channels etc, & doesn't work for practical channel. In [65], a large scale MIMO detector is proposed which uses a DNN and a low-density parity-check (LDPC) code for working. In [66], a neural network based MIMO detection technique is developed and it is found out that DNN works better than convolutional neural networks (CNNs). Also, this MIMO detector is shown to provide better BER performance & robustness than ZF, MMSE and DetNet detectors even when the channel conditions are not perfectly known. In [67], a deep CNN based network is proposed for removing the effects of correlated noise environments in MIMO detectors. It can be used with any linear MIMO detector such as ZF, MMSE, etc. Similarly, in [68], a deep CNN network is proposed to be used along with an ML detector to suppress interference in vehicular MIMO networks. Further, in [69], an improved version of OAMPNet, termed as OAMPNet2 was developed. However, even though its performance was 5 dB better than OAMPNet, it was only able to work for unitarily-invariant channels and shows poor performance for realistic channels. It also had higher complexity than OAMP-Net.

MMNet, which is a deep learning based massive MIMO detector, is ten times less computationally expensive and even then achieves the same error rate performance as OAMPNet [70]. Though it works for massive MIMO detection, its hardware implementation has yet to be studied and corresponding challenges have to be solved. It has the ability to work with any type of channel but since it requires online retraining, it is very computationally expensive. In [71], an extra neural network which taken in channel input and outputs weights of the detector, called hypernetwork is added to the neural network-based MIMO detector. The combination is called HyperMIMO and it achieves a performance close to that of MMNet trained for each channel realization, and outperforms OAMPNet. It is robust to user mobility up to a certain point, which is encouraging for practical use.

In [72], a learning to learn iterative search algorithm (LISA) is proposed for the detection of signals in MIMO. It shows better performance than ZF, MMSE, MMNet, and DetNet MIMO detectors. A BiLSTM-DetNet (BD-Net) is developed in [73] that shows better performance than DetNet and is easier to train comparatively. In [74], to overcome the limitations of the existing DL-based MIMO detectors, such as low convergence speed and low robustness to new scenarios, a new MIMO receiver that supports training in online mode is proposed. For this EPNet and TurboNet are developed along with an LSTM-based online training method for meta-learning. In [75], a recurrent neural network (RNN) - reservoir computing (RC) MIMO-OFDM detector called RCNet is developed which performs online training. In [76], a recurrent equivariant MIMO detector (RE-MIMO) is developed which shows robustness towards misspecification of the channel and is extendable for any number of users. It shows better symbol error rate (SER) performance than OAMPNet, SDR, AMP, DetNet, etc. It has to be tested for more realistic channels before further deployment. In [77], a variational Bayesian inference based MIMO detector, termed VBINet is developed and it shows better performance than OAMPNet and MMNet as it has the ability to learn noise variance from the given data.

In [78], the already existing EPNet is enhanced by utilizing a hypernetwork and developing the new HyperEPNet MIMO detector. In [79], SRN, a low complexity, deep unfolded sparse refinement network based on mMIMO uplink detection is shown to have good performance in terms of BER. In [80], a dynamic neural network (DyNN) is developed for the enhancement of the efficiency and lowering of the cost of computation in the wireless communication network. Also, two improved versions of DetNet are proposed, i.e., a confidence criterion-based dynamic improved DetNet (CD-IDetNet) and a policy network-based dynamic improved DetNet (PD-IDetNet). These have the advantage of reducing computational complexity and still achieving good accuracy. In [81], a model-driven MIMO OFDM detector, known as conjugate gradient OAMPNet (CG-OAMPNet) is developed, which is an improved version of the OAMPNet in terms of complexity.

In [82], for MIMO OFDM detection, a structure-based neural network, termed as RC-Sruct which uses reservoir computing(RC) is developed. When rank and link adaptation is used, its benefits over current techniques become more obvious. With regard to 5G/5G-Advanced and beyond, the newly announced RC-Struct provides insight into how to combine communication domain knowledge with learning-based receive processing. In [83], a real-time learning DL-based MIMO OFDM detector is constructed by using RNN and extreme machine learning (ELM). In [84], an improved version of ADMM-based DNN is developed to reduce the computational complexity which is termed a penalized ML problem via the sharing-alternating direction method of multipliers (PS-ADMMNet). Though it performs better than DetNet, MMSE, and several ADMM-based detectors, it has more run time complexity. Further, a penalized sharing-ADMM detector with a hidden layer network (PS-ADMM-HNet) is also developed. Though it has less computational time complexity than PS-ADMMNet, its performance falls behind it. In [85], a real-time ML-enhanced AMP massive MIMO detector, termed as LAMANet is developed which shows better performance than previous DL-based detectors such as OAMPNet, MMNet etc. A lot of research work has been and is being conducted for developing the best possible MIMO detector and AI plays an important role in it. Before deployment of these AI based MIMO detectors, the challenges discussed in this paper have to be addressed. Further, for other types of MIMO scenarios, such as cell-free mMIMO, distributed MIMO etc, work has to be done in future for development of efficient detection algorithms.

VI. CONCLUSIONS

A review of various types of methods and techniques for MIMO detection has been discussed in detail in this paper. The problem of MIMO detection has been discussed in detail which is followed by the need of development of a MIMO detector which is both computationally efficient and accurate. The role of AI in designing of MIMO detectors has been discussed along with some of the AI based detectors, their challenges and their advantages. It has been highlighted that for deployment of AI based MIMO detectors, a lot of improvement has to be done and the existing challenges have to be resolved.

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