Deep Learning in Physical Layer Communications

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Abstract

With advancements in IoT taking place at an exponential rate, the number of communication devices is expected to increase immensely. This places a heavy importance on reliable communication between devices. The existing structure and implementation of physical layer communication suffers from delays and results in a sub-optimal performance. This structure of communications can be viewed as blocks of functionality that serve to perform a task. These blocks of focused functionality result in optimization issues when transitioning from one block to another, and as well as within the block of feature space. This paper discusses the origin of deep learning neural networks, the approach and construction of neural networks, along with the physical aspects needed to be taken into consideration in design in physical layer communications. It demonstrates how the existing design implementations which are based on mathematical frameworks rely heavily on assumptions that do not entirely translate to real world environments and result in the degradation of the performance in the Physical Layer mechanisms functionality. The paper discusses how the inclusion of deep learning could present solutions to this suboptimal functioning decision making. It also presents potential use cases and applications for Deep Learning, strengthening its stance as the next logical step in the advancements for Physical Layer communications.

Keywords

Deep Learning, Feature Extraction, Feature Selection, Design Aspects, Neural Networks, Physical Layer, Real-World Environment

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1. Introduction

The first conceptualization of deep learning can be dated back to the early 1940s. Industry experts, McCulloch and Pitts made attempts to show that a Turing machine program could be implemented in a finite network of neurons, briefly introducing us to neural networking theory. In the late 1940s, McCulloch in his paper "How We Know Universals: The Perception of Auditory and Visual Forms" offered an approach to designing nervous sets.[Pitts47]

This initiated the movement towards constructing neural networks which serve as the foundation for deep learning. The underlying methodology for deep learning builds on the core instruction of using deep neural networks to discover how data is organized and represented at each layer within the network. To create a working neural network, data needs to be built at each level and several techniques can be utilized to accomplish this. These machine learning techniques can be divided into three different are Supervised Machine Learning, Unsupervised Machine Learning, and Reinforcement Learning.

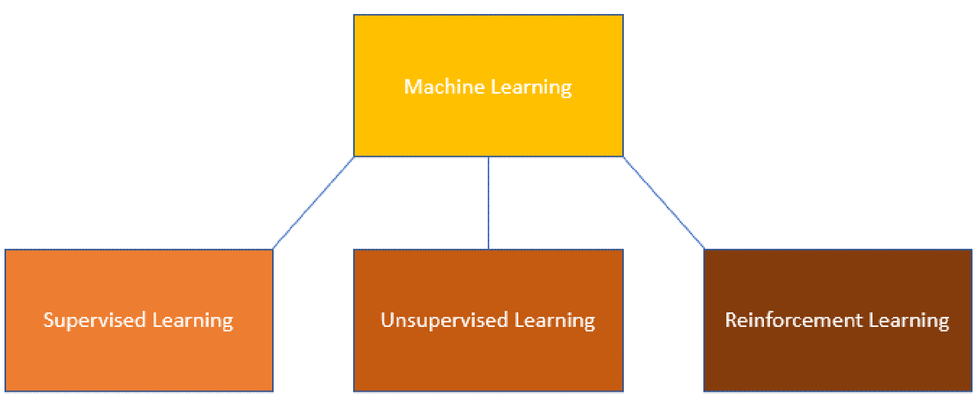

Figure 1: Machine Learning Methods

Communications in networking cover a broad range of functionality, ranging from channel modeling to designing optimal signaling and detection schemes that ensure reliable data transfer. These areas within communications suffer from diminishing returns when it comes to performance improvements, especially within the physical layer, and can be streamline placing a major emphasis on signal processing.

Conventional communication systems are based on mathematical models that have proven to achieve optimality. Theoretically, we can achieve an optimal solution that is constructed by the mathematical framework but when practically applied, we experience sub-optimal results due to external factors such as correlations or delays that the actual system in a real-world setting pose. This sheds light on the structure of the communication system architecture.

Typically, digital communication systems contain several processing blocks at the transmitter and receiver sides: equalization, bandpass signaling, channel coding, multiplexing, and multiple access. We can view the structure of the communication system as a group of systems or blocks requiring consecutive decision mechanisms that at each level serve to reduce a larger problem into smaller subproblems, where each subproblem is structured as a decision problem.

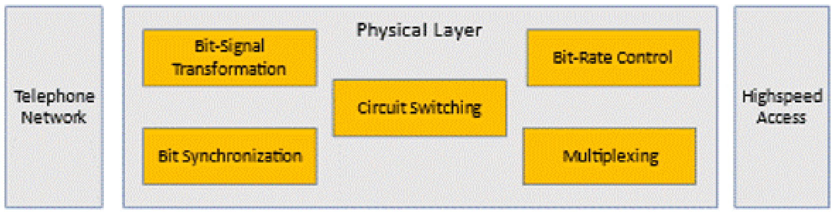

Figure 2: Communications Mechanisms

These individual blocks are designed separately to achieve optimal results within their domain. Therefore, this approach of subsystem optimization cannot guarantee a global sense of optimization throughout the system. An example of a problem faced in a specific real-world setting is modeling underwater acoustic channels or molecular communication which requires a more adaptive framework to handle the external environmental changes and challenges that they pose. To counter the performance challenges posed by the current non-adaptive conventional system, Deep Learning is expected to play a vital role in increasing - in a holistic sense - performance yields and allowing the theoretical models to be more tuned and perform flexibly in real-world applications.

2. WHY DEEP LEARNING AT THE PHYSICAL LAYER?

This section discusses the tools that deep learning offers at the physical layer. Deep Learning comes into play in situations where mathematical expressions are unable to formulate an all-encompassing solution. Mathematical formulations created and simulations conducted by researchers rely on assumptions which server to simplify the problem statement in order to achieve a closed form expression. While achieving these formulations through performing assumptions works out well in confined simulation environments, they do not yield similar results when put in a real-world environment. Deep Learning Neural Network models come in to solve this issue. Deep Learning offers a unique solution to these continuously changing adaptive environments and deep learning neural networks play a big role.

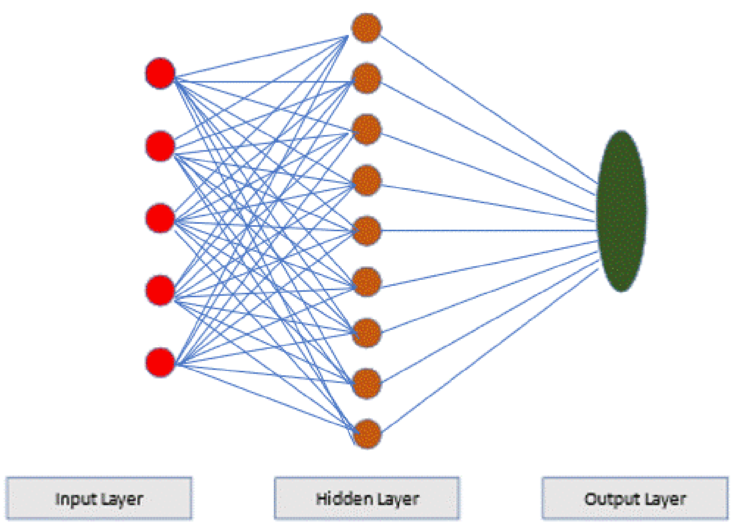

Figure 3: Deep Learning Neural Network

Deep Learning Neural Networks are being used as a tool to solve issues on address handover and power management in physical layer functionalities such as cellular networks, dynamic spectrum access, resource allocation, caching, video streaming, and rate adaptation.

Conversely, traditional machine learning methods which use a feature-based approach have not been instrumental due to the limitations that they pose. They pose limitations by creating excessive HW consumption, and feature extraction limitations, and do not permit real-time fine-tuning. Deep Learning's approach of using neural networks relieves the burden of determining the necessary features. This is crucial as it allows a High Dimensional Feature Space, All-In-One Approach, and Real-Time Fine Tuning.

Furthermore, Deep Learning driven models possess the ability to rectify the challenges posed forward by the mismatch that occurs between real systems and theoretical models by using a data-driven approach to increase the adaptive nature of the models. They can continuously self-evolve and improve to cater to the specifications of the situation at hand. This increased autonomy within the PHY decision mechanisms decreases human interference and provides a longer-term solution.

2.1 High-Dimensional Feature Spaces

The incorporation of Deep Learning Neural Networks in the physical layer architecture paves way for a high-dimensional feature space. Having a high-dimensional feature space is a leap when it comes to dividing waves into more unique classifications. With the permittance of a high-dimensional feature space, the waves can be divided into smaller, finer units and serve to showcase a greater distinction. We know this because waves are distinguished by determining the differences in the patterns that exist in their in-phase quadrature. Traditionally, in radio fingerprinting the conventional model distinguished up to a few dozen devices. With Deep Learning based architecture, 100s of devices can be classified by training our model to adapt to and learn from the small-scale complexities that continuously change in the I/Q space [Francesco22].

2.2 All-In-One Approach

Another benefit of having a DL-based structure is the All-In-One Approach. The DL-based system enables automatic feature extraction which permits the reuse of the same DL architecture for different learning problems that exist in the physical layer. This, in turn, contributes to reusing the same hardware architecture for the Deep Learning system. The Neural Networks in Deep Learning based model are extracting information in the I/Q plane, accessing small-scale, very detailed, and fine information. Learning from these I/Q patterns, information within the DL can be viewed as abstract and used to solve different problems. To achieve such a model, the decision of where the deep learning happens is an important decision to be made by the architects [Francesco22].

An example of this would be using Deep Learning based systems where a system is trained to classify modulation, the number of carriers, and fingerprinting. To perform these three functions using traditional machine learning techniques, we are required to construct different hardware for all three functions which individually extract features specific to the function description. The use of DL enables this All-In-One approach which allows us to navigate past the barriers laid out by traditional techniques [Francesco22].

2.3 Real-Time Fine Tuning

As previously mentioned, the existing system is built on a set of assumptions and modeled to specific requirements. The problem that arises with this sort of modeling is when the model experiences situations that it was not expecting. In turn, the expected performance takes a hit in these situations as the model-driven system does not achieve the yields that were expected [Francesco22].

An example of such a situation is a model constructed on the assumption of Rayleigh fading channels. If this model instead experiences Rician fading channels, it will not adapt to this change in environment and result in incorrect solutions. The incorporation of Physical Layer Deep Learning gives our system a data-driven approach to be more adaptable to changing environments. It does this by using fresh spectrum data to find more fitting parameters in real-time through gradient descent. This allows the model to be tuned in real-time to yield optimized results and is one of the most important advantages of having deep learning-based systems [Francesco22].

Real-Time fine-tuning cannot be obtained using traditional machine learning techniques because of the limitations of adjustment posed by the existing hardware in practice. Therefore, DL is the best way to achieve this [Francesco22].

3. PHYSICAL LAYER DESIGN ASPECTS

This section discusses the design aspect of the physical layer. These aspects are necessary to understand the structure of the physical layer communication are five design aspects that need to be considered for Physical Layer mechanisms.

3.1 Synchronization

Synchronization is crucial when it comes to transmission accuracy between transmitter and receiver processes. An important factor in synchronization is for the receiver to be able to timely detect the transmitted signal and compensate for the oscillator's phase and frequency errors. The underlying assumption when crafting these models is that there exists perfect synchronization between the transmitter and receiver. However, in actual real-world situations, this is not the case. There always exist residual synchronization errors caused by Radio Frequency front-end impairments, delays, changing mobility, and the variance in channel conditions. Systems yield suboptimal results due to the unknown nature of propagation delays, channel interference, and RF impairments [Gecgel22].

3.2 Channel Estimation Errors

Understanding the PHY processing steps requires a thorough understanding of channel estimates. Correlation, maximum likelihood, maximum a posteriori, or least-squares-based estimators can all be used to determine the channel. Once more, these techniques are based on presumptions that do not always pan out in the real world. For instance, traditional systems consider quantization error to be nonexistent and believe that Analog to Digital Converters have infinite resolution. The availability of instantaneous feedback information, interpolation mistakes, and estimated flaws that lead to round-off errors must all be overcome by real systems. Massive antennas, 3-Dimensional deployments, and high mobility scenarios will make the impact of estimation errors on performance more severe since they will cause the channel conditions in future networks to change quickly [Gecgel22].

3.3 Erroneous Feedback Information

Feedback Information is very important to successfully coordinate the transmitter and receiver. There exists a discrepancy between the forward and backward links when processing the feedback information as both cannot exist simultaneously. There also exists a delay in feedback on its practical implementation. An example of this is in the selection of antennas and beamforming. All variations must be included to select the optimal settings. These considerations are necessary when designing the feedback part, and to achieve higher accuracy of the optimal mathematical models, intelligent learning algorithms seem to be the best candidates for solving these problems [Gecgel22].

3.4 RF Front-end Impairments

RF front-end impairments are caused by three things: In-Phase. Quadrature-Phase Imbalance, Phase Noise, and Non-Linearities. IQ Imbalance of phase between in-phase and quadrature-phase components. Phase Noise makes frequency adjustments difficult. The frequencies fluctuate and cause common Phase Errors and Inter Carrier Interface. Non-linearities pose another important barrier in achieving optimality and are usually assumed to not be a concern when theoretically modeling the Physical layer functionalities [Gecgel22].

3.5 Correlation

Correlation is another design aspect that needs to be considered when designing the architecture of physical layer. Since the architecture can be viewed as blocks of decision-making functions, these blocks require an efficient method to translate the outputs as inputs to the other blocks. Formulating correlations becomes challenging as it holds great potential to lead to inaccuracies in the physical layer. Formulating correlations can require a continuous tracing of frequency, domains, and time which adds to the complexity of the structure at large and becomes challenging [Gecgel22].

4. CHALLENGES

It is apparent that the future of physical layer decision mechanisms must adhere to the practical complexities that are experienced when these mechanisms are implemented in real-world situations. Existing implementations do not adapt well to problems that are caused by synchronization, feedback links, channel estimations, correlations, and RF impairments. It is expected that in the future, communication systems will become unique, experiencing incredible adversity about changing conditions. The existing theoretical models will suffer from their inability to match the actual conditions which the system will endure. This eventual mismatch will be the major limiting factor for reaching the target goals set forth.

Challenges specific to the implementation of Deep Learning Neural Networks have much to do with the efficiency of their computation. The neural networks must execute quickly to avoid the challenges that can be posed by the overflowing of the I/Q buffer. This challenge that is faced in the construction of Deep Neural Networks must operate faster than the channel's coherence time. They must also be efficient enough to make decisions that can happen before the frequency of the transmitter changes its parameters.

4.1 Data Scarcity

Since Deep Learning is a data-driven approach, its instruction relies heavily on the availability of data. With the reduced availability of data, the ultimate problem that can be run into using DL-based modeling is overfitting of the model and this leads to failure in real-time situations. Data scarcity can occur in some fields and not in others.

For example, data may not be available in certain areas due to privacy, security, and confidentiality concerns. A solution to these areas could be the use of open-source data sets or encrypting datasets for decision learning. In other areas, there are only really two approaches that can be taken to solve data scarcity: 1. Increasing the amount of data available 2. Reducing the need for big data. Data can be increased by augmentation techniques. And conversely, reducing the need for big data can be applied to very specific smaller scale problems. However, the latter can only serve as an immediate solution and not offer a longer-term solution [Gecgel22].

To make data more readily available, a proposed direction would be to create wireless data factories that can generate In-Phase/Quadrature waves data at a very large scale. This would make verified useful data available for decision learning in Physical layer Deep Learning models. However, once the data is available, we are posed with the hardware implementation challenges of incorporating DL into models [Gecgel22].

Some neural network models also make use of fake datasets which could be a solution to this problem. The Generative Adversarial Net and Conditional GAN is an approach which essentially creates data based on a specific target distribution. This can reduce the demand for a larger data set [OShea17].

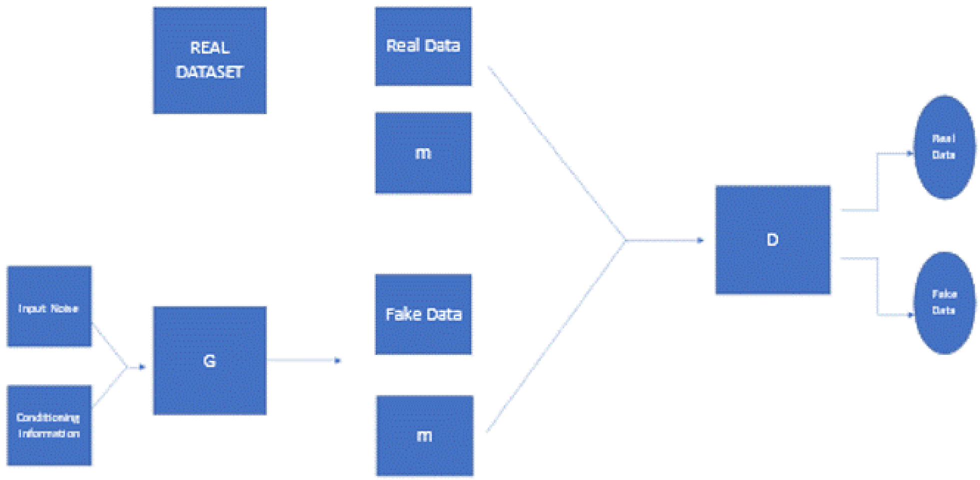

Figure 4: Generative Adversarial Net

4.2 Feature Extraction or Selection

Feature extraction and selection are the most vital areas that impact the performance of learning algorithms. They serve to make the representations of data better. Feature selection is used to describe data that resides in the lower-dimensional space by removing irrelevant and repetitive data points - in part to aid computationally intensive datasets. Conversely, feature extraction is rather a more general approach to creating useful features using the existing data set.

In existing models of the architecture, the feature space cannot hold many distinguished wave patterns. Given this issue, there is a lot less variation in wave patterns and thus there is a lack of classifications and distinctions between different patterns. This reduces the problem-solving capability as there is -for a lack of better words - decreased room for finer detail.[Kim20]

4.3 Computational complexities

There are two stages in the deep learning mechanism that would be applied to the physical layer. The first is the training of the model on the given data set. The second is the prediction of the model based on an unknown data set using the training in the previous step. While these are common to conventional machine learning as well, Deep Learning Neural Network techniques using loss functions on adjusted weight sets extracted from labeled datasets have proved to be instrumental in reducing the complexities. This has been achieved by incorporating techniques such as transfer learning and computational offloading. In fact, through experimentation, we have come to learn that less complex algorithms have proven to achieve higher accuracy. [Gecgel22]

4.4 Hardware Limitations

Deep Learning methods require large amounts of processing power, physical size, cost, and memory. The demands from hardware to provide all the above-mentioned resources implement learning algorithms difficult as it creates computation complex and difficult especially with regards to efficiency. Cloud platforms propose a solution for this problem by removing the load from the hardware. However, this introduces a new problem - fast, efficient communication between the cloud and the user and ultimately adds to the load and existing layers of the communication system, resulting in decreased optimization.

4.5 Security

Security is by far the most challenging problem in Physical Layer Deep Learning modeling. Vulnerabilities exist in maintaining the authenticity of datasets and upholding the integrity of the user information. The model can thus be vulnerable to poison attacks and evasion attacks as Deep Learning relies heavily on large datasets. These attacks can affect learning-driven solution algorithms and mislead the algorithms to produce incorrect outputs. Learning-driven algorithms do possess the capabilities of increasing security through their adaptive nature, but a concrete solution is yet to be proposed. [He22]

5. DEEP LEARNING IN PHYSICAL LAYER APPLICATIONS

5.1 Analyzing Ultra-Wide Spectrum Bands

Tera Hertz and millimeter Wave frequency bands have now become the leading contenders for 5Giga-Bit communications. They operate with ultra-wide spectrum bands. The existing pilot-based channel estimation does not possess the capability to reach the optimal level of performance. This occurs due to the continuous transmission of pilots for the entire bandwidth which results in an overall loss of throughput. Deep Learning Neural Networks can play a significant role in this situation. Similarly, instead of always increasing the number of pilots, a neural network could be trained to infer the channel directly based on the I/Q samples [Francesco22].

5.2 Wireless Channel Estimation: Deep Neural Network Augmented Wireless Channel Estimation on System on Chip

Existing channel estimation techniques rely on conventional frameworks proposed in Shannon's theory, detection theory, and queuing theory. These frameworks in practical implementation experience performance degradation due to the unprecedented variation that exists in the wireless environment. Deep Learning through its ability to automatically select features from datasets proposes a viable solution that possesses the ability to improve the performance results.

Currently, several techniques can accomplish this. We will briefly introduce and discuss the works of one technique - Local Salient Deep Neural Network - based on channel estimation and some of its design details to better understand the architecture of DNN and its implementation. This model like any other Neural Network model possesses a layered structure [Mubarak22].

This Deep Learning Neural Network uses augmented Least Squares estimation. The output is processed by the LS estimator using the Deep Neural Network, reducing the effect of noise on LS estimates. Compared to existing channel estimating techniques, this model performs better due to its ability or the ability of DNN to automatically extract the necessary channel features and through its learning ability to output a meaningful analysis of the datasets. This technique navigates around the erroneous channel parameters which are the cause of degradation in Linear Minimum Mean Square Error performance. Its Deep Learning Neural Network does not require erroneous knowledge and thus can be used to avoid the expected overhead, performing better [Mubarak22].

The architecture of this model serves to accomplish 5 tasks: 1) Data Extraction, LS-Based channel estimation, 3) Pre-processing, 4) DNN, and 5) post processing. Long Term Samples are extracted at the receiver side from the data set collected post OFDM demodulation. These symbols that are extracted contain real and imaginary parts. These are inputted to the LS estimators which perform mathematical computations. This output of the LS estimators is then processed by the DNN architecture. Before sending data into the DNN architecture, the data needs to be pre-processed [Mubarak22].

We will take a deeper dive into the structure of this DNN. The DNN architecture for the application of wireless channel estimation - taken from the ***- consists of several hidden layers and an output layer. It has a fully connected DNN, implying that each neuron in a given layer connects to each output in the subsequent layer, with multiple processing elements. An important thing to note here which is true for all DNN models is that Data communication takes place only in the forward direction. Therefore, there is no communication between neurons grouped in the same layer. Blocks of Rectified Linear Activation function are added ahead of each hidden layer to introduce non-linearity. Once the bias additions and ReLU operations have been performed, the next layer within the neural network is activated. This process is repeated until the output layer is reached [Mubarak22].

5.3 Security: Deep Learning-Based Channel Reciprocity Learning for Physical Layer Secret Key Generation.

Physical layer key generation is a known encryption approach in wireless systems. This approach can serve to improve the security of wireless networks. Deep Learning can be applied to replace the existing approaches that are used in physical layer key generation. These approaches use manual feature extraction techniques which result in performance degradation and security vulnerabilities when implemented in real-world situations.

Through the works of He, Chen, and Huang, we are introduced to a deep learning approach to generating physical layer secret key generation. In their paper "Deep Learning-Based Channel Reciprocity Learning for Physical Layer Secret Key Generation", they propose an approach to extract highly consistent keys from imperfect channel responses, leveraging channel reciprocity through Deep Learning. They mention how to design a neural network for efficiently learning channel reciprocity features from wireless channels that exist in Time Division Duplex Orthogonal Frequency Division Multiplexing systems. This is further leveraged to create a new key-generation scheme based on the proposed neural network model, resulting in a superior key-generation rate, key-error rate, and randomness [He22].

Again, the exploitation of large feature space and automatic selection - qualities of Deep Learning Neural Networks - have been used to develop functionalities that are better suited to real world application.

5.4 Deep Learning based Autoencoder for m-User Wireless Interference Channel Physical Layer Design

Another application within the physical layer is the use of deep learning in autoencoding for m-User Wireless Interference Channel Physical

Layer Design. The Deep Learning based Autoencoding offers a new approach to physical layer design using a data-driven, end-to-end learning-based solution. Conventional auto-encoding has relied on the muti-block structure. However, in situations where the environment experiences a high interference the conventional model does not perform well [Wu20].

In the paper "Deep Learning-Based Autoencoder m-User Wireless Interference Channel Physical Layer Design" published by Wu, Nekovee, Wang, a novel approach is proposed to construct and implement an adaptive Deep Learning based Autoencoder. Dynamic interference can be learned and predicted and the learning processing for the decoder is updated. The conventional system uses n-Quadrature Amplitude Modulation schemes with zero force and minimum mean square error equalizer and performs poorly when presented with an environment with high interference. This proposed model takes advantage of the automatic feature selection and extraction offered by deep learning and achieves a significant Big Error Rate in extremely high interference environments [Wu20].

The paper also states that the Deep Learning based autoencoding has through this approach paved the way for generating optimal adaptable constellation for 5G and beyond communication systems.

6. Summary

In this paper we have introduced deep learning as a potential solver of the several optimzation problems that currently exist in the architecture of the physical layer communications. In this paper, we demonstrate the potential use of Deep Learning in the Physical Layer and in great depth talk about its importance to the Physical Layer mechanisms. The main emphasis is laid on the benefits and improvements it offers to the area of physical layer communications in comparison to the existing structure. We shed light on the physical layer design aspects: synchronization, channel estimation errors, erroneous feedback information, RF Front-end impairments, and correlation which need to be considered in carrying out a successful implementation. This technique comes with its own set of challenges: Data Scarcity, Feature Extraction or Selection, Computational complexities, Hardware Limitations, and Security. We have also stated some of its potential applications to serve as an example of how and where deep learning can be used and implemented, demonstrating a means to understand its applicability in focused areas. We hope to convey through our paper that deep learning is in fact the next logical step in advancing physical layer communications.

7. References

[Pitts47] Pitts, W. and McCulloch, W.S., 1947. How we know universals the perception of auditory and visual forms. The Bulletin of mathematical biophysics, 9(3), pp.127-147, https://link.springer.com/article/10.1007/BF02478291

[He19] H. He, S. Jin, C. -K. Wen, F. Gao, G. Y. Li and Z. Xu, "Model-Driven Deep Learning for Physical Layer Communications," in IEEE Wireless Communications, vol. 26, no. 5, pp. 77-83, October 2019, doi: 10.1109/MWC.2019.1800447,https://ieeexplore.ieee.org/abstract/document/8715338

[Syed20] Ali, S., Saad, W., Rajatheva, N., Chang, K., Steinbach, D., Sliwa, B., Wietfeld, C., Mei, K., Shiri, H., Zepernick, H.J. and Chu, T.M.C., 2020. 6G white paper on machine learning in wireless communication networks. arXiv preprint arXiv:2004.13875,https://arxiv.org/abs/2004.13875

[OShea17] T. O'Shea and J. Hoydis, "An Introduction to Deep Learning for the Physical Layer," in IEEE Transactions on Cognitive Communications and Networking, vol. 3, no. 4, pp. 563-575, Dec. 2017, doi:

10.1109/TCCN.2017.2758370,https://ieeexplore.ieee.org/abstract/document/8054694

[Qin19] Z. Qin, H. Ye, G. Y. Li and B. -H. F. Juang, "Deep Learning in Physical Layer Communications," in IEEE Wireless Communications, vol. 26, no. 2, pp. 93-99, April 2019, doi: 10.1109/MWC.2019.1800601,https://ieeexplore.ieee.org/abstract/document/8663966

[Kim20] H. Kim, S. Oh and P. Viswanath, "Physical Layer Communication via Deep Learning," in IEEE Journal on Selected Areas in Information Theory, vol. 1, no. 1, pp. 5-18, May 2020, doi: 10.1109/JSAIT.2020.2991562,https://ieeexplore.ieee.org/abstract/document/9085350

[Bhattacharya21] Bhattacharya, P., Bodkhe, U., Zuhair, M., Rashid, M., Liu, X., Verma, A. and Kishan Dewangan, R., 2021. Amalgamation of blockchain and sixth-generation-envisioned responsive edge orchestration in future cellular vehicle-to-anything ecosystems: Opportunities and challenges. Transactions on Emerging Telecommunications Technologies, p.e4410,https://onlinelibrary.wiley.com/doi/abs/10.1002/ett.4410

[Francesco22] Francesco Restuccia and Tommaso Melodia. 2022. Toward Polymorphic Internet of Things Receivers Through Real-Time Waveform-Level Deep Learning. GetMobile: Mobile Comp. and Comm. 25, 3 (September 2021), 28-33., https://doi.org/10.1145/3511285.3511294

[Gecgel22] S. Gecgel Cetin, C. Goztepe, G. K. Kurt and H. Yanikomeroglu, "A Glimpse of Physical Layer Decision Mechanisms: Facts, Challenges, and Remedies," in IEEE Open Journal of the Communications Society, vol. 3, pp. 1280-1294, 2022, doi: 10.1109/OJCOMS.2022.3195434,https://ieeexplore.ieee.org/abstract/document/9845678

[Mubarak22] Mubarak S. Almutairi, "Deep Learning-Based Solutions for 5G Network and 5G-Enabled Internet of Vehicles: Advances, Meta-Data Analysis, and Future Direction", Mathematical Problems in Engineering, vol. 2022, Article ID 6855435, 27 pages, 2022. ,https://doi.org/10.1155/2022/6855435

[Francesco20] Francesco Restuccia and Tommaso Melodia. 2020. PolymoRF: polymorphic wireless receivers through physical-layer deep learning. In Proceedings of the Twenty-First International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing (Mobihoc '20). Association for Computing Machinery, New York, NY, USA, 271-280. ,https://doi.org/10.1145/3397166.3409132

[Gecgel21] Gecgel, Selen, Caner Goztepe, Gunes Karabulut Kurt, and Halim Yanikomeroglu. "Learning-Driven Decision Mechanisms in Physical Layer: Facts, Challenges, and Remedies." arXiv preprint arXiv:2102.07258 (2021),https://arxiv.org/abs/2102.07258

[Wu20] D. Wu, M. Nekovee and Y. Wang, "Deep Learning-Based Autoencoder for m-User Wireless Interference Channel Physical Layer Design," in IEEE Access, vol. 8, pp. 174679-174691, 2020, doi: 10.1109/ACCESS.2020.3025597,https://ieeexplore.ieee.org/abstract/document/9204706

[Restuccia20] Restuccia, F. and Melodia, T., 2020. Deep learning at the physical layer: system challenges and applications to 5G and beyond. IEEE Communications Magazine, 58(10), pp.58-64,https://ieeexplore.ieee.org/abstract/document/9247524

[He22] He, H., Chen, Y., Huang, X., Xing, M., Li, Y., Xing, B. and Chen, L., 2022. Deep Learning-Based Channel Reciprocity Learning for Physical Layer Secret Key Generation. Security and Communication Networks, 2022,https://www.hindawi.com/journals/scn/2022/1844345/

[Gizzini22] Gizzini, Abdul Karim, Shakti Shrey, Sumit J. Darak, Sneh Saurabh, and Marwa Chafii. "Deep Neural Network Augmented Wireless Channel Estimation on System on Chip." arXiv preprint arXiv:2209.02213 (2022),https://arxiv.org/abs/2209.02213

8. List of Acronyms

Acronym	Definition
IoT	Internet of Things
HW	hardware
PHY	physical layer
I/Q	In-Phase Quadrature
DL	Deep Learning
RF	Radio Frequency
ADC	Analog to Digital Converters
ICI	Inter-Carrier Interface
GAN	Generative Adversarial Net
THz	TeraHertz
LS	Least Squares
DNN	Deep Neural Network
QAM	Quadrature Amplitude Modulation
LTS	Long Training Symbols
ReLU	Rectified Linear Activation Function

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