Applications of Deep Learning for Millimeter Wave

Saveeta Bai
Electronic Engineering Department
Sir Syed University of Engineering and
Technology
Karachi, Pakistan
saveetahari4@gmail.com

Muhammad Rauf
Department of Electronic Engineering
Dawood University of Engineering and
Technology,
Karachi, Pakistan
muhammad.rauf@duet.edu.pk

Abid Muhammad Khan
Electrical Engineering Department
Sir Syed University of Engineering and
Technology
Karachi, Pakistan
abidmk@ssuet.edu.pk

Suresh Kumar
Department of Electronic Engineering
Universitat Politècnica de Catalunya
Barcelona, Spain
suresh.kkes@gmail.com

Haresh Kumar
Electronic Engineering Department
Sir Syed University of Engineering and
Technology
Karachi, Pakistan
hkumar@ssuet.edu.pk

Engr. Agha Ali Mirza
Electrical Engineering Department
Sir Syed University of Engineering and
Technology
Karachi, Pakistan
mamirza@ssuet.edu.pk

Abstract—Millimeter Wave (mm-wave) has been considered as significant importance in various communication systems. It has achieved a greater attention to meet the capacity requirement of the future 5G network. Since mm-wave has a high frequency (30 to 300 GHz) using orthodox technologies for mm wave is more challenging. Thus advanced technology i.e. Deep Learning (DL) is a pragmatic approach to analyze a massive amount of data. Firstly, to find out how DL has beaten traditional approaches, this review briefly explores, the different methods of DL for mm wave are. Secondly, the review of the multiple applications in mm wave such as beam and blockages prediction, beam spacing, beamforming for mm wave OFDM system, precoding for mm-wave, channel estimation for mm-wave, sparse channel estimation, and hybrid precoding and fingerprinting-based indoor localization with mm wave is concisely explained. Last but not least, several studies have proved that DL has superior efficiency for mm wave than conventional approaches.

Index Terms—Artificial Intelligence, Deep Learning, Machine Learning, Millimeter Wave.

I. INTRODUCTION

Artificial Intelligence (AI) is a comprehensive approach to make machines to perceive how smart human perceive. AI has a subfield that is known as Machine Learning (ML), which basically make the prediction on unseen data by learning fundamental statistical arrangements in data. Deep Learning (DL) is a second picture of ML that is originated from it and uses multi-layered mathematical processes in order to learn and infer on massive data like imagery [1]. Moreover, from the complex and complicated data sets, extracting the universal features, is also among its unique abilities. Comparing DL with other machine learning techniques, it has revealed enhanced performance in numerous

errands and tasks [2] such as natural language processing (NLP) [3]. DL is most widely used approach that elevates a deep neural network (DNN) that can map relationships approximately that are not known or non-linear. Hence, it is frequently implemented in the wireless communications systems for modulation [4], detection [5, 6] to estimate the channel, non-orthogonal multiple access (NOMA), massive multiple-input multiple-output (MIMO) systems [7], etc. Furthermore, from web surfing to content filtering such as on social networks, in order to recommend the websites based on e-commerce solutions, and it is significantly presented in products of consumer for instance, smartphones, smart watches and cameras etc. DL also identifies the images consist of objects, converts recorded speech into text, matches news items, filter out the posts or products related to user's level of interest and selects only those results of search that are most relevant with a significant accuracy. These advantages have allowed DL to become an emerging approach that can proficiently resolve numerous problems in medical [8], with the great promises of DL technology, the application of DL has been promoted to pharmaceutical research, including drug discovery [9].

For 5G network, millimeter wave (mm Wave) is one of the significant technologies to maximize the data rate [10]. The frequency range of mm wave lies between 30Hz and 300 GHz where a total of around 250 GHz bandwidths are accessible. It ranges within the super high frequency band and the far infrared band, whereas the terahertz band is dedicated for lower part. In this band the wavelength of radio waves ranges from ten to one millimeter, so in this way it is also called the millimeter band and millimeter waves are the radiations in this band. Even though the accessible bandwidth of mm Wave frequencies is more challenging, there is a significant difference in propagation characteristics from microwave frequency bands which could lead to path loss, blockage

and diffraction, atmospheric absorption, rain attenuation, and foliage loss behaviors. Generally, the overall loss of mm wave systems is expressively bigger than that of microwave systems for a point-to-point link. Due to technology's poor propagation characteristics, it is a daunting challenge to overcome these losses by traditional approaches thus several different strategies the of DL method have been applied for mm wave. In the communication systems, mm wave meets high data rate requirements because of its bandwidth. Conversely, channel estimation, hybrid precoding, beam and blockage prediction, and beam training are more challenging by using conventional methods. Therefore, the major contribution of this work are to compare conventional methods with the deep learning-based methods and show that the deep learning techniques are superior and more advantageous over other traditional techniques[10, 11]. In addition, the literature of applications of deep learning for mm wave is categorized based on method types and objective.

In the past, in order to reduce computational complexity and poor performance of the mmWave massive MIMO systems conventional mathematical approaches such as channel state information (CSI) [12], singular value decomposition (SVD), geometric mean decomposition (GMD) [13] and in a massive MIMO, compressive sensing (CS) detectors were applied which are insufficient to utilize the sparsity data of the mmWave system. Deep learning is recently emerged as a new solution, is a very extraordinary technology to deal with enormous extents of data and solving complex and multipart nonlinear matters and issues. Deep learning (DL) has been presented to be an effective tool for solving the problems and coping with situations such as non-convex that require a lot of computing concerns, to which it devotes its superlative recognition and the representation ability.

II. BASIC PRINCIPLES OF DEEP LEARNING AND NEURAL NETWORK

Machine Learning (ML): DL is a subset of ML [14], so first the basic concepts of ML are introduced. ML is one method to analyze data that identifies patterns in the data and then uses these patterns to predict future results. ML methods have three main classes that have been discussed below [15].

A. Supervised Learning (SL)

In Supervised Learning (SL) the training sets are mainly composed of couples of input and intended output, with the objective of learning a mapping between the inputs and outputs. The inputs are 2D points, the outputs are the labels (circles or crosses) that are allocated to every input while aiming to build a binary classifier. Examples of applications include channel decoder and e-mail [16].

B. Unsupervised Learning (UL)

The data set is composed of UL inputs that are unlabeled, that is, inputs that have no assigned desired outcome. The inputs are once again points in the 2D plane, but the data provides no hint of the desired output.

The goal of UL is to uncover properties of the system that generates the data in general. The purpose of UL is to make an association of input points those are adjacent to one other, so each input point is given a label – the cluster index (dashed lines delimit the clusters). It emphasizes that clustering is merely one of the learning activities included in the UL category [17].

C. Reinforcement Learning (RL)

Under certain contexts, RL bridges the gap between supervised and unsupervised learning. In contrast to unsupervised learning, there is some form of supervision, but it does not take the form of specifying a desired outcome for each input in the data. Instead, after the determination of an output with respect to specific input or observation, a reinforcement learning system receives feedback from the environment. The feedback reflects the how efficient the output is, also known as action in the RL meets learner's requirements. RL is used to sequential decision making problems in which learner interact with the environment by consecutively performing actions (outputs) based on observations(inputs) while receiving feedback on each act [18].

The Basic Concept of Deep Neural Network (NN): In Artificial Intelligence (AI), DL is a subtype of ML, i.e., it is able to implement functions that are used to replicate the functionality of the human brain by creating patterns and processing data, and it is based on artificial neural networks (NN) and representation learning [19]. DL is also used for decision making in fields like self-driving car (to identify pedestrians, street lights, other cars, etc.), to recognize speech, to analyzed image (e.g. Finding cancer in blood and tumors), smart TV, etc.

With several iterations of data processing, through the learning and relearning procedure algorithms such as DNN can be greatly tuned. NNs augment Artificial Intelligence. Radial Basis Function (RBF), Feed Forward NN, Convolutional Neural Network (CNN), Multiplayer Perceptron, Recurrent Neural Network (RNN), Sequence to Sequence Model and Modular Neural Network (MNN) are among various types of NNs existed.

1) *Feed-Forward NN*: It is also known as the most common neural network (NN) that exists almost everywhere in the domains like NN. This network literally moves forward, as its name suggests, and it does so until it reaches the output node. It helps and enhances the nodes in different layers, without any back feedback and there isn't much in the way of self-learning. Figure 1 shows a one-layer NN with a simple depiction [20].

Fig. 1 Representation of FFNN (Feed-Forward Neural Network)

2) *Radial Basis Function (RBF) Neural Network*: The distance between data points and center is the main notion in these sorts of NNs. These NNs usually have two layers among which one layer is hidden while second one is the output layer. The radial basis function of the hidden layer is conventional. This function assists acceptable interpolation while fitting data to the model. This is based on the assumption that the points those are closer together, are also similar in nature and possesses a k-NN-like association. In this way the output of an item that is targeted and predicted, will perform in the same way to other items that have more similarity in the context of the predictor variables as the intuition goes [21].

3) *Multilayer Perceptron*: The Basic Concept of Deep Neural Network (NN) In Artificial Intelligence (AI), DL is a subtype of ML, i.e., it is able to implement functions that are used to replicate the functionality of the human brain by creating patterns and processing data, and it is based on artificial neural networks (NN) and representation learning [19]. DL is also used for decision making in fields like self-driving car (to identify pedestrians, street lights, other cars, etc.), to recognize speech, to analyzed image (e.g. Finding cancer in blood and tumors), smart TV, etc. With several iterations of data processing, through the learning and relearning procedure algorithms such as DNN can be greatly tuned. NNs augment Artificial Intelligence. Radial Basis Function (RBF), Feed Forward NN, Convolutional Neural Network (CNN), Multiplayer Perceptron, Recurrent Neural Network (RNN), Sequence to Sequence Model and Modular Neural Network (MNN) are among various types of NNs existed.

Fig. 2 Multilayer Perceptron

4) *Convolutional Neural Network (CNN)*: Convolutional Neural Network is more advanced version of Multilayer Perceptron. There is one or more convolutional layers in this kind. The fundamental question is: What is meant by the convolutional layer? It is simply a purifying mechanism or a filtration process that allows for activation. Such filtering process offers the position and power of a recognized feature when it is repeated. In technologies image processing, neural languages and recommender systems, usually these networks are employed. As a result of their ability to produce effective results of the crucial characteristic discovered [11].

5) *Recurrent Neural Network (RNN)*: As it is implied by its name, something recurs in this system of network. The output of this specific layer in this network is preserved and then pointed back to feed it towards the input again. In this case, Feed-Forward Neural Network is considered as the first layer with every node, retaining information in later levels. Just in case if the forecast is incorrect, the system of such network will repeat the process of learning and in order to make the correct prediction it learns very well. It is a common conversion method that is used in i.e. text-to-speech methods. The memory storage is the building block of this system of network, which will also have an impact on the better prediction of what will happen next [23].

6) *Modular Neural Network*: This kind of Neural Network is the last but not least type of neural network. The basic building block of this neural network is modularity, as the name implies. Modularity refers to the ability of distinct networks to carryout sub-tasks independently one another, and because they do not interact, computation speed increases. This allows enormous complicated processes to run more rapidly and faster by processing individual module. This is as similar as independently the left and right side of the brain manages things autonomously, yet be one, a Modular

neural network is a corresponding state to this natural biological network system [24]

III. APPLICATIONS OF DEEP LEARNING WORK

There are various applications of deep learning which are thoroughly reviewed and discussed in this section. Deep learning is further divided in sub-categories some are discussed in following literature review.

A. *Deep Learning Assisted Regulated Beam Training for mm Wave in Communication Systems*

Three calibrated beam training approaches with DL assistance (CNN, LSTM and adaptive beam training) has been discussed here in this section. The direction of narrow beam will be calibrated as according to the channel power leakage while using a wide beam that is based on DL training method. Finally, in order to deal with the channel power leakage's complex nonlinear features, DL is used to estimate the ideal narrow beam directly.

In [25], three calibrated beam training approaches with DL assistance are proposed.

- A CNN-based technique for predicting the beam that is based on the real time received signals. As the predicted outcomes are presented in terms of probability so each narrow beam candidate is the optimum one. Additionally, to calibrate further beam directions, narrow beam training with respect to the probabilities probability prediction may be performed.
- LSTM technique, which utilizes received signals from earlier beam training to track the movement or progress of the UE and ultimately regulate the course of beam.
- To train in an adaptive beam training techniques -based on previously acknowledged signal that is received- partially wide beams are selected. In adaptive wide training two approaches Optimal Neighboring Criterion (ONC) and Maximum Probability Criterion (MPC) are chosen. Wide beams those are adjacent to each other and related to proposed optimal beam, are picked by ONC, whereas MPC picks the wide beams with the nearest estimated probabilities.

Simulation results exhibit that when comparing with the traditional existed deep learning based complements, our suggested approaches can obtain considerably much larger gain of beamforming that too with reduced beam training overhead.

B. *AI-Driven 6G mm Wave Networks based on Deep Learning (DL) for Fast and Consistent Primary Access*

In [26], DeepIA, framework having a DNN for allowing reliable and quick primary access for AI-driven beyond the networks such as 5G and 6G mmWave. In this paper authors have also suggested that the beam sweep time may also be minimized through Deep AI, by the utilization of small part of available beams. When comparing this sweep time with a traditional IA algorithm that also behaves as exhaustive search, it shows that DeepIA is more efficient. To reduce the sweep time of beam AI should only use a subfield of the available beams. From the subset of beams, received signal strengths (RSSs) are achieved and mapped to the beam and this beam is best orientated towards the receiver side by DeepIA. DeepIA decreases IA time and performs much better than the conventional or traditional IA's beam especially the prediction accuracy of line of sight (LoS) and non-line of sight (NLoS) situations. Two techniques are compared in this work, CBS and DeepIA by using several numbers of beams and demonstrate that, DeepIA has much faster and reliable IA scheme along with this it also offers more reliability particularly in scenario of accurate prediction. For instance, optimum beam with near to 95% accuracy is predicted by DeepIA, in the case of LoS it is done by sweeping only 7 among all 24 beams. Whereas the precision of the CBS for the same setting is limited to 24%. While a CBS method would conventionally not use a subclass of beams, nonetheless, authors implement it in this fashion to obtain a fair comparison between the accuracy and input size of the two methods.

C. *Index Modulation Aided mm Wave Systems based on Detection by Deep Learning Assisted Method*

Neural Network (NN): In [27], the authors presented and demonstrated the index modulation millimeter wave (mm wave) systems by the utilization of deep learning assisted detection. Here concurrently detection of transmission and index information are performed by a neural network (NN) that is not reliant on explicit channel state information (CSI). MS-STSK was first used, and also the design was studied by the association of the MS-STSK transmission and BIM. Learning-assisted detection, unlike the MS-traditional STSK's detector, avoids the estimation stage of channel, ultimately makes it more spectral-efficient as compared to the ML detection. Furthermore, the Neural Network's weight is recalibrated in order to increase the efficiency of fidelity in learning assisted detection after certain amount of frames. The NN that has been recalibrated, requires fewer number of side and training information known to the receiver and transmitter. And it is shown that overhead required for training is minor as compared to overhead pilots required for channel estimation.

D. DL based mm Wave Beam and Prediction of Blockage using Sub Channels of 6GHz

Deep Neural Network (DNN): The authors have demonstrated in [15], about the mapping functions through which may ideally forecast the millimeter wave beam and the status of blockage straight from the sub-6 GHz channel under specific situations. However, for quantifying analytically these mapping functions are difficult hence DNN models are used to train them. It has been demonstrated that a large enough NN can anticipate millimeter wave beams and blockages by means of success probabilities arbitrarily near to ideal i.e. one. The authors present a neural network (NN) that can accomplish the tasks of predictions over sub-6GHz channels. They use precise 3D ray tracing so that to produce estimation of datasets and examine the network. Finally, it performs both tasks when properly trained with appropriate data, that too with a high level of reliability, ultimately resulting in promising and impressive results, particularly when noisy channels are presented like sub-6GHz channels.

E. Channel Estimation for mmWave based on Deep CNN Massive MIMO Systems

Spatial Frequency CNN (SF-CNN): Hybrid processing architecture is commonly employed in millimeter wave (mmWave) large multiple input multiple output (MIMO) systems to minimize entanglement and expense, which poses a problematic work in channel estimation. In [11], deep CNN is employed to address this problem. At neighboring subcarriers, the distorted channel matrices are simultaneously input into the CNN in a spatial frequency CNN (SF-CNN) based channel estimation (CE) leveraging both of the spatial and frequency correlation. Then, to increase accuracy even further, a spatial-frequency-temporal CNN (SFT-CNN) based approach is created, which takes use of temporal correlation in time-varying channels. Furthermore, a spatial pilot-reduced CNN (SPR-CNN) is meant to reduce spatial pilot overhead for channel estimation by grouping and estimating channels in many subsequent coherence intervals using a channel estimation unit with memory.

F. Millimeter Wave Beam-Selection based on DL; LIDAR Data

Convolutional Neural Network (CNN): LIDAR data may be utilized for detection of line-of-sight and as well as in reduction of the overhead assumed to be in mm wave beam-selection [17]. Even the position of base station is also broadcasted by itself through such proposed architectures in this case it is Distributed Architecture. The associated vehicle influences its LIDAR data to propose a set of beams based on selection through a convolutional NN rather it can be associated with the term deep Convolution. Here Authors also have solved key problems in the LIDAR (mm Wave system) by using the

ML. Firstly they identified that either the channel is in LOS or in NLOS condition either by developing a predictor to examine this condition. Also it is provoked that in the LOS setting the beam-selection is going to be much easier when detected the LOS. Later on secondly, they use both DL and NN as a combined tool that is trained to achieve the classification of Top-M those conditioned on LOS and NLOS state approximations.

G. Beam Management and Interference Coordination based on Deep learning (In the Dense mm wave Networks)

DNN (Deep Neural Network): Now the algorithms, those require more complexity in terms of computational power; intended to increase the entire network specifically sum-rate, along this, algorithm like RRM are usually needed to achieve the good estimations and results again the complexity is considered to be one of the important factor among such tasks. Authors then have proposed beam management that is based on DL, in order to highlight this challenge. He also has proposed the method suitable for mm wave network (Dense) i.e. Interference coordination method (BM-IC), that finally led towards the transformation of BM-IC algorithm that were more conventional and complex, into an efficient approximations based on DNN. This is because of the fact that series of calculations (e.g., multiplications and additions) are needed in the DNN only needed though the complexity of computation is finally reduced [18]. The beam management and interference coordination (BM-IC) is performed by using the DL in the case of dense mm wave specifically wireless local area networks (WLAN) along with the architecture that is also centralized. Through this proposed method e.g. DL, those in-depth patterns hidden may also be extracted layer by layer from the input data. Moreover, the training data from the suggested BFT data aided BM-IC procedure is achieved so get data can be obtained approximately by driven DNN model for the proposed method. Last but not least, the obtained DNN model is used to perform BMIC densely mmWave network in actual-time. It could be differentiating from the predominant deep learning-based wireless network optimization studies, the suggested deep learning-based BM-IC technique can enhance the beam directions, beam widths and simultaneously transmit the power of each beam.

H. Applications of DL for the Channel Estimation for Beam space mm Wave Massive MIMO Systems

Convolutional Neural Network (CNN): In the beam space mm wave that is based on massive multiple inputs and outputs system, and if the receiver is equipped with a very few and limited quantity of radio frequency (RF) chains then estimation of Channel, faces more challenges. To overcome this delinquent, researcher exploit another network such as learned denoising-based approximate message passing (LDAMP). By this way structure of channel and estimation can be learned by NN can learn

from the large quantity of training data. Additionally, an investigative analytical framework is also provided based on the asymptotic performance of the channel estimator [19]. A massive number of training data for channel estimation and for learning structure. 2D natural image

are known as Channel matrix. In this way to integrate the denoising convolutional neural network (DnCNN) into the iterative sparse signal recovery algorithm for channel estimation, the LDAMP neural network is applied.

Table 1 Comparison of Several proposed DL Schemes with respect to their application and corresponding pros

Year	Application	DL Scheme	Leads in term of Pros
2021[25]	For mm wave communication system based on DL aided attuned and calibrated beam training.	CNN LSTM Adaptive beam training strategy	<ul style="list-style-type: none"> Higher gain of beamforming Smaller overhead in beam training
2021[26]	Fast and Trustworthy Initial Access such as in AI-Driven 6G mm wave Networks again based on DL	DNN	<ul style="list-style-type: none"> Reduced time, needed for initial access through Deep IA. Overall cost especially Operational one is also reduced by Deep IA. It lessens the number of broadcasts/beams. –ultimately decreases the interfering from/to other ongoing broadcasts and transmissions.
2020[27]	Deep Learning Assisted Detection system for Index Modulation Aided mm wave Systems	Multi-set space-time shift keying (MS-STSK)	<ul style="list-style-type: none"> The detection based on learning assisted overtakes the ML-aided detection where the channel impairments through less complexity
2020[28]	Millimeter Wave Beam and Blockage Prediction Using Sub-6GHz Channels through the Deep Learning	Mapping functions through DNN	<ul style="list-style-type: none"> More than 90% of probability in terms of successfully prediction of blockages in mm. Achieving the upper bounds without consuming the beam training overhead, by predicting the optimal and ideal mm Wave beams.
2019[11]	Estimations of Channel for mm Wave Massive MIMO Systems based on Deep CNN	CNN 1. (SF-CNN) 2. (SFT-CNN) CE	<ul style="list-style-type: none"> Complexity is reduced Healthy and robust Effective and efficient Performance of estimation is improved.
2019[29]	mm wave Beam-Selection based on Deep Learning-Based and LIDAR Data	Classification of DL for top-M.	<ul style="list-style-type: none"> The ability to receive those clouds from the high-density point in relative shorter time duration while maintaining the vertical accuracy and cost effect is one the big advantage by the use of LiDAR over old-style and conventional photogrammetry
2018[30]	Beam Management and Interference Coordination (BM-IC) based on Deep Learning for Dense mm wave.	BM-IC an alternative method that is based on DL (Deep Learning).	<ul style="list-style-type: none"> In BM-IC less computing time is required to gain the sum-rate specifically in dense mm wave network based on DNN, ultimately dramatically decreases the overheads in terms of computational abilities in real time applications.
2018[31]	The Estimation of Channel for Beam space mm wave Systems based on Massive MIMO.	The neural network consisted of LDAMP.	<ul style="list-style-type: none"> Easier to train Multiple selection network can use this. While having limited number of RF at receiver's side, excellent performance may be achieved by the LDAMP network, and this implies and validates its practicality and applicability.

IV. ANALYSIS OF RESPONSES

Literature shows that advanced technology i.e. DL has superior efficiency than traditional methods. Moreover, applications of DL for mm wave have promising results as can be analyzed in Table 1. For instance, reduced training data set size, better accuracy and less computation running time.

In Figure 3 prediction accuracy is analyzed. DeepIA and the baseline CBS is also compared with each other in [32] in the context of their performances. Moreover, the accuracy of prediction in LOS and NLOS, has been also compared within the same context. In CBS, the exhaustive beam search is dependent on scanning the whole spatial plane, its precision constantly declines as fewer beams are employed. Whereas on the other side, the demonstration of more reliable and robust predictions of accurateness over the range of swept beams goes in the favor of DeepIA. Besides this, the assessment of performance of mmWave massive MIMO technique is carried out that is based on DNN in order to estimate the dominance of the anticipated approach.

Fig. 3 DeepIA versus CBS for mm Wave path loss models such as LoS and NLoS [32]

The performance of the BER DNN-based method, is also compared with those of the hybrid precoding technique based on singular value decomposition (SVD) have also been investigated [33], additionally also the other precoding methods those based on fully digital

SVD, fully geometric mean decomposition (GMD) and also the new GMD [34]. Methods such as DL-based, work more efficiently over the traditional and conventional schemes, and can be analyzed in Figure.4. Furthermore, the improved performance is extra obvious among the approach and conventional methods based on DL, which is endorsed to the outstanding representation ability of DL. In addition, since the structural information is exploited by DNN and for hybrid precoding where every iteration of the algorithm may be approached, it is proved that precoding methods such as fully GMD-based digital, are not superior then the proposed mmWave massive MIMO strategy, inferring that the existing hybrid precoding based on non-convex optimization may also be determined by the help of DL. The performance of the suggested mmWave massive MIMO scheme has been carried out through the comprehensive investigation as shown in figure 5. Moreover, the efficiency of spectrum performance is shown in terms of the SNR of the DNN that are based on the schemes like spatially sparse method, fully digital GMD based and hybrid precoding. Also it can be observed that as the SNR increases, spectrum efficiency is also improved in all the techniques and may be depicted from the figure. 5. Moreover, it may be analyzed that such precoding scheme in this case hybrid, leaves all other methods behind it, ultimately gains enhanced hybrid precoding performance devoted by the incomparable mapping and learning limits and capacities of the DL. Moreover, the scheme based on DL and that of other approaches their gap of performance is appropriate larger when the SNR upsurges, the performance gap of the. This superior performance further predicts the efficiency of the proposed such hybrid precoding scheme [35]. Whereas the performance comparisons of different channel estimation methods may be observed in Figure. 6. Also, the D-AMP algorithms and the denoising (earned)those are based on approximate message passing (LDAMP) network hence the support detection (SD) is outperformed and compares analysis approximate message passing algorithms like SCAMPI due to the denoisers those are powerful enough. Moreover, the network such as LDAMP performs more efficiently then the state-of-the-art D-AMP algorithms whereas for signal revival or recovery in a compressive way, the BM3D-AMP is considered to be the most precise algorithm. And the DL technology turned out to be more superior only when the large number of training data is utilized and attributed by the networks such as the powerful network LDAMP.

Fig. 4 DNN based scheme BER and SNR

Fig. 5 proposed DL

Fig. 6 Comparison of performance (NMSE) v/s other methods i.e. LDAMP network.

In case of DNN based scheme BER and SNR. Moreover, in case of hybrid precoding scheme (SVD based)[33], wholly digital precoding methods based on SVD, GMD and also new GMD based)[34]. In case of proposed DL, efficiency of spectrum versus SNR. DL is based on based digital GMD, hybrid precoding scheme and the spatially sparse precoding method.

V. CONCLUSION

Applications for mm wave using conventional methods in the communication system are oriented for last two decades. This paper provides literature review of multiple applications of DL for mm wave, different techniques of DL NN used for mm wave and brief review of methodologies of DL schemes as well. Since mm wave has extremely high frequency due to this fact it could lead to numerous losses such as blockage, atmospheric absorption, path loss, and diffraction, rain Fade (attenuation) and foliage loss behaviors. Therefore, literature shows that the significant performance of DL NN for mm wave with better efficiency, high accuracy and reduced cost. Theoretically mm wave has substantial amount of bandwidth. However, practically these improvements are insignificant task, according to physics the radiation propagation at these frequencies change intensely. The conventional geometrical methods are unreliable for NLOS positions for outdoor positioning. Thus, these limitation promotes application of deep learning techniques in order to obtain more accuracy for outdoor positioning. But there are some limitations for DL NN (convolutional network) such as, average error corrections NLOS millimeter wave outdoor positions, moderate bandwidth, binary data samples, and a single anchor. The future extension of the presented schemes is, it would be fascinating to develop learning models that can handle environmental dynamics as well as examine the practical conditions under which the objectiveness conditions are disrupted, and design more proficient and practical deep learning based approaches for mm wave system. Therefore, literature shows that the significant performance of DL NN for mm wave with better efficiency, high accuracy and reduced cost. Theoretically mm wave has substantial amount of bandwidth. However, practically these improvements are insignificant task, according to physics the radiation propagation at these frequencies change intensely. The conventional geometrical methods are unreliable for NLOS positions for outdoor positioning. Thus, these limitation promote the applications of DL systems in order to obtain more accuracy for outdoor positioning. But there are some limitations for DL NN (convolutional network) such as, average error corrections NLOS millimeter wave outdoor locations, moderate bandwidth, binary data samples, and a single anchor. The future extension of the presented schemes is, it would be fascinating to evolve learning models that can manage environmental dynamics as well as examine the real time conditions under which the objectiveness conditions are

disrupted, and design more proficient and practical deep learning based approaches for mm wave system. Therefore, literature shows that the significant performance of DL NN for mm wave with better efficiency, high accuracy and reduced cost.

REFERENCES

- [1] Schwendicke, F.a., W. Samek, and J. Krois, Artificial intelligence in dentistry: chances and challenges. *Journal of dental research*, 2020. 99(7): p. 769-774.
- [2] LeCun, Y., Y. Bengio, and G. Hinton, Deep learning. *nature*, 2015. 521(7553): p. 436-444.
- [3] Schmidhuber, J., Deep learning in neural networks: An overview. *Neural networks*, 2015. 61: p. 85-117.
- [4] O'shea, T. and J. Hoydis, An introduction to deep learning for the physical layer. *IEEE Transactions on Cognitive Communications and Networking*, 2017. 3(4): p. 563-575.
- [5] Soltani, M., et al., Deep learning-based channel estimation. *IEEE Communications Letters*, 2019. 23(4): p. 652-655.
- [6] Ye, H., G.Y. Li, and B.-H. Juang, Power of deep learning for channel estimation and signal detection in OFDM systems. *IEEE Wireless Communications Letters*, 2017. 7(1): p. 114-117.
- [7] Huang, H., et al., Deep learning for physical-layer 5G wireless techniques: Opportunities, challenges and solutions. *IEEE Wireless Communications*, 2019. 27(1): p. 214-222.
- [8] Miotto, R., et al., Deep learning for healthcare: review, opportunities and challenges. *Briefings in bioinformatics*, 2018. 19(6): p. 1236-1246.
- [9] Chen, H., et al., The rise of deep learning in drug discovery. *Drug discovery today*, 2018. 23(6): p. 1241-1250.
- [10] Sim, M.S., et al., Deep learning-based mmWave beam selection for 5G NR/6G with sub-6 GHz channel information: Algorithms and prototype validation. *IEEE Access*, 2020. 8: p. 51634-51646.
- [11] Dong, P., et al., Deep CNN-based channel estimation for mmWave massive MIMO systems. *IEEE Journal of Selected Topics in Signal Processing*, 2019. 13(5): p. 989-1000.
- [12] Chen, C.-H., et al., Compressive sensing (CS) assisted low-complexity beamspace hybrid precoding for millimeter-wave MIMO systems. *IEEE Transactions on Signal Processing*, 2016. 65(6): p. 1412-1424.
- [13] Chen, C.-E., Y.-C. Tsai, and C.-H. Yang, An iterative geometric mean decomposition algorithm for MIMO communications systems. *IEEE Transactions on Wireless Communications*, 2014. 14(1): p. 343-352.
- [14] Jang, H.-J. and K.-O. Cho, Applications of deep learning for the analysis of medical data. *Archives of pharmacal research*, 2019. 42(6): p. 492-504.
- [15] Ayodele, T.O., Types of machine learning algorithms. *New advances in machine learning*, 2010. 3: p. 19-48.
- [16] Figueirêdo, I.S., et al. Detecting Interesting and Anomalous Patterns In Multivariate Time-Series Data in an Offshore Platform Using Unsupervised Learning. in *Offshore Technology Conference*. 2021. OnePetro.
- [17] Eteläpää, A., WCD-20 spark diagnostic. 2021.
- [18] Heuillet, A., F. Couthouis, and N. Díaz-Rodríguez, Explainability in deep reinforcement learning. *Knowledge-Based Systems*, 2021. 214: p. 106685.
- [19] O'Donovan, C., C. Giannetti, and G. Todeschini. A Novel Deep Learning Power Quality Disturbance Classification Method using Autoencoders. in *ICAART* (2). 2021.
- [20] Hamandi, S., A.M. Rahma, and R. Hassan, Multi-Spectral Hybrid Invariant Moments Fusion Technique for Face Identification. *Int. Arab J. Inf. Technol*, 2021. 18(3A): p. 405-413.

- [21] Hannan, S.A., R. Manza, and R. Ramteke, Generalized regression neural network and radial basis function for heart disease diagnosis. *International Journal of Computer Applications*, 2010. 7(13): p. 7-13.
- [22] Taravat, A., et al., Multilayer perceptron neural networks model for meteosat second generation SEVIRI daytime cloud masking. *Remote Sensing*, 2015. 7(2): p. 1529-1539.
- [23] Yin, W., et al., Comparative study of CNN and RNN for natural language processing. *arXiv preprint arXiv:1702.01923*, 2017.
- [24] Qiao, J., X. Guo, and W. Li, An online self-organizing modular neural network for nonlinear system modeling. *Applied Soft Computing*, 2020. 97: p. 106777.
- [25] Ma, K., et al., Deep Learning Assisted Calibrated Beam Training for Millimeter-Wave Communication Systems. *arXiv preprint arXiv:2101.05206*, 2021.
- [26] Cousik, T.S., et al., Deep Learning for Fast and Reliable Initial Access in AI-Driven 6G mmWave Networks. *arXiv preprint arXiv:2101.01847*, 2021.
- [27] Katla, S., et al., Deep Learning Assisted Detection for Index Modulation Aided mmWave Systems. *IEEE Access*, 2020. 8: p. 202738-202754.
- [28] Alrabeiah, M. and A. Alkhateeb, Deep learning for mmWave beam and blockage prediction using Sub-6 GHz channels. *IEEE Transactions on Communications*, 2020. 68(9): p. 5504-5518.
- [29] Klautau, A., N. González-Prelcic, and R.W. Heath, LIDAR data for deep learning-based mmWave beam-selection. *IEEE Wireless Communications Letters*, 2019. 8(3): p. 909-912.
- [30] Zhou, P., et al., Deep learning-based beam management and interference coordination in dense mmWave networks. *IEEE Transactions on Vehicular Technology*, 2018. 68(1): p. 592-603.
- [31] He, H., et al., Deep learning-based channel estimation for beamspace mmWave massive MIMO systems. *IEEE Wireless Communications Letters*, 2018. 7(5): p. 852-855.
- [32] Cousik, T.S., et al., Fast initial access with deep learning for beam prediction in 5G mmWave networks. *arXiv preprint arXiv:2006.12653*, 2020.
- [33] El Ayach, O., et al., Spatially sparse precoding in millimeter wave MIMO systems. *IEEE transactions on wireless communications*, 2014. 13(3): p. 1499-1513.
- [34] Xie, T., et al., Geometric mean decomposition based hybrid precoding for millimeter-wave massive MIMO. *China Communications*, 2018. 15(5): p. 229-238.
- [35] Huang, H., et al., Deep-learning-based millimeter-wave massive MIMO for hybrid precoding. *IEEE Transactions on Vehicular Technology*, 2019. 68(3): p. 3027-3032.