Al-Salam Journal for Engineering and Technology
Journal Homepage: http://journal.alsalam.edu.iq/index.php/ajest
e-ISSN: 2790-4822 p-ISSN: 2958-0862

# A comprehensive overview of machine learning-assisted antenna for modern wireless communication

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DOI: https://doi.org/10.55145/ajest.2024.03.01.004
Received June 2023; Accepted August 2023; Available online September 2023

**ABSTRACT:** In this work, an overview of implementing machine learning (ML) models in antenna design and optimisation has been proposed. This includes deep learning on ML structure, categories, and frameworks to obtain useful and general insights about methods of predicting, collecting, and analysing high throughput fast data using ML techniques. An in-depth overview on the various published research works related to designing and optimising of antennas using ML is proposed, including the different ML- techniques and algorithms that have been used to generate antenna parameters such as S-parameters, radiation pattern, and gain values. However, the designing of modern antennae is still complicated regarding structure, variables, and environmental factors. Moreover, the cost of time and computational resources are unavoidable and unacceptable for most users. To address these challenges, ML methods-based antennas have been developed and applied to improve the reduction in the efficiency and accuracy of antenna modelling. This can be involved methods to rain models on data that can be utilised to predict the antenna performance for a given set of antenna design variables. This work summarises the developed and applied MLs that have been proposed to improve the efficiency and accuracy of antenna modelling.

**Keywords:** machine learning, ANNS, antenna

## 1. INTRODUCTION

In the 5G era, wireless communication technology has gained significant attention, making antenna design crucial in communication. To optimize antenna design and develop more efficient, versatile, and directional high-gain antennas, researchers have explored various methods such as novel feed structures, changing the number and arrangement of antennas in the array, adjusting antenna polarization, and replacing specific elements. However, most conventional antenna design methods involve changing geometrical characteristics to find the optimal state for a specific frequency band, which requires several attempts to analyze and adjust, taking significant time and effort [1-4].

Machines are becoming more and more like humans in their decision-making, problem-solving, learning and other functions. Machine learning is a method of automating the building of analytical models by analyzing data, and deep learning (DL) enables machines to mimic human actions and behaviors by processing data. These techniques have many advantages, including optimization of complex antenna performance. Machine learning and deep learning can be used to create many pre-trained models for antenna design applications, making antenna design more efficient and faster. Recent research has focused on the application of ML and DL to a variety of antenna design problems, including mmWave, centrosome, terahertz, satellite, UAV, GPS, and textiles. For example, they arable antennas enable human-to-human communication through body-centric technology, and terahertz frequencies can be used for various fields of spectroscopy. Satellites orbiting the Earth broadcast communication signals, but UAVs can fly without an operator on

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the ground. Without ML and DL, coil designs are less maintainable, less defective, and more productive. Without DL and ML support, simulating, maintaining work feasibility, and calculating antenna behavior is a very difficult task that loses control, and textile technology consists of textile fibers. Focus on textile fabrics.

The authors of this article discuss the use of reinforcement learning (RL) algorithms to improve the average data rate in multi-antenna wireless systems and implement hybrid beamforming in the mmWave frequency band. They use machine learning techniques to optimize beam pair selection in wireless communication systems, integrating previous beam training information such as receiver position, closest vehicle, and receiver size to train the model and identify the optimal beam pair index. To research on mmWave or Massive MIMO antennas, a dataset is needed and dedicated datasets are provided with information [1,7,18].

For multi-user mm-Wave systems, the researchers in [19] developed a hybrid beamforming (BF) architecture in which the number of active elements (AEs) employed in a BF base station per user changes with distance. They also created a machine learning framework to teach beamforming codes for large-scale MIMO systems that are responsive to the environment. A description of millimeter wave channel principles and an explanation of how to categorize map-based channels are given in [25]. [34] created a non-portable handheld communications system employing industry-standard components such omnidirectional antennas, network interfaces, and Wi-Fi routers. The same authors [25] also cover map-based channel categorization and millimeter wave channel models.

In this research, a group of researches in the field of machine learning and potential applications are compared, and the importance of using machine learning applications will be discussed with a regression of their importance in predicting values after training a model on a set of database extracted from several designs that will be tested to demonstrate the importance of improving the design using Machine learning techniques, the most important of which is multiple regression.

## 2. Utilizing ML and DL in various Antenna Designs Applications

ML and DL have proven to be highly effective in various applications, including but not limited to THz, UAV, Satellite technologies, textile, and GPS. Their ability to learn representations in real-world environments has made them ideal for many applications. One such application is the utilization of ML in UAVs in civilian and other purposes. Additionally, body-centric communications system as they ll leverage ML and DL to enhance their abilities. In accordance with the data provided by [7], (Table 1).

**Table 1. - Different classifiers' Impact on Probability of Beam Selection Alignment and achieved the throughput Ratio [25]**

| Method | $P_A$(%) | $P_r$(%) |
|---|---|---|
| Random forest | 85.14 | 98.32 |
| Gradient Boosting | 69.05 | 96.49 |
| Naïve -Bayes | 59.14 | 91.14 |
| RBF-SVM | 55.89 | 89.32 |
| As a Boost | 45.8 | 75.05 |

### 2.1 ML and DL techniques in millimeters wave (mm-Wave) applications for antenna design

The mm-Wave frequency range, which falls betthey en (30-300 GHz) or (1-cm) to (1-mm) in wave-length, is advantageous for data transmission and sensing systems. With its large unlicensed bandwidth, mm-Wave technology has various applications in different fields. Many wireless applications rely on mm-Wave antennas, which can be made more flexible with using ML algorithms. Machine Learning tools have proven useful for each massive MIMO and mm-Wave antenna design. Hybrid beam forming, which requires a big antenna array to the systems of mm-Wave, it's also discussed in this section.

#### 2.1.1 Hybrid Wireless Systems Beam-forming Algorithms by DL

A hybrid beamforming algorithm called the mmWave Massive MIMO system is used in the mm-wave frequency spectrum to increase an average data rates of multi- wireless antenna networks. It is made up of two components: an analog beamformer and a digital precoder. The former connects the transmit antenna to the RF block's output, while the latter does the same for parallel streams of input symbols. There are numerous approaches to construct hybrid beamforming schemes, including Reinforcement Learning (RL), which evaluates candidate solutions' effectiveness using a Machine Learning (ML) algorithm. The RL algorithm produces results that are comparable to those of a brute force search in terms of sum data rates, but it goes through fethiye iterations.

#### 2.1.2 Situational Awareness mm-Wave Vehicle Beam Training

The framework for machine learning with context-sensitive implementation was proposed in this paper. The best beam pair index was predicted using three different techniques, taking into account GPS error, location error, and connected vehicle penetration variations. The beam selection path's comprehensive evaluation was introduced, with a particular emphasis on the alignment probability and throughput matrices. The efficiency of prediction was assessed by altering the number of automobiles in the feature. The paper also discusses the noise properties of a few real-world issues, with Random Forest meeting alignment probability of 85.14 percent. Although acquisition throughputs were not statistically different from one another, they did not scale with alignment likelihood. Finding good beams was made possible by the model's accuracy, and it was notably helpful to achieve reduced overhead at the sacrifice of optimality.

### 2.1.3 Beam Alignment at Massive MIMO at mm-Wave

A base station (BS) for multi-stream systems may manage numerous users with multiple beams since Mm-Wave is a short form factor that can be packed into a tiny form factor employing big antenna arrays. A hierarchical codebook is not essential for aligning beams for the large number for users, however beam training depends on theoretical codebooks frequently used to tune beams for different users. The mm-Wave channel model is used to train AMPBML NNs offline in a simulated environment. The NN is then deployed live and the incomplete beams are used to estimate the beam distribution vector. For multi-user mm-wave Massive MIMO systems, this work also developed a partial beam alignment mechanism using AMPB ML, which exhibits superior performance to previous techniques [11].

### 2.1.4 An mm-Wave Massive MIMO

Mm-Wave MIMO is a promising solution for future communications, as it combines digital precoding and hybrid analogs to reduce hardware complexity and pother consumption. This work uses a deep learning architecture to optimize hybrid precoder specification as a mapping relation (DNN) to reduce bit error rate and increase spectral feasibility. Hybrid precoding outperforms traditional methods, but requires less computation, and a framework is created using DNN and deep networks as auto-coders. DNN can reduce computation time during training phase, collecting structural features of the hybrid precoding scheme. A DNN-based millimeter-wave Massive MIMO scheme was developed by Keras and analyzed using numerical analysis to investigate its performance. BER performance was compared to common techniques and analyzed at different training data sets batch sizes and learning rates. Statistical feasibility results were presented for all-digital GMD-based precoding schemes, SNR for a hybrid precoding scheme, and a spatially sparse precoding method [12].

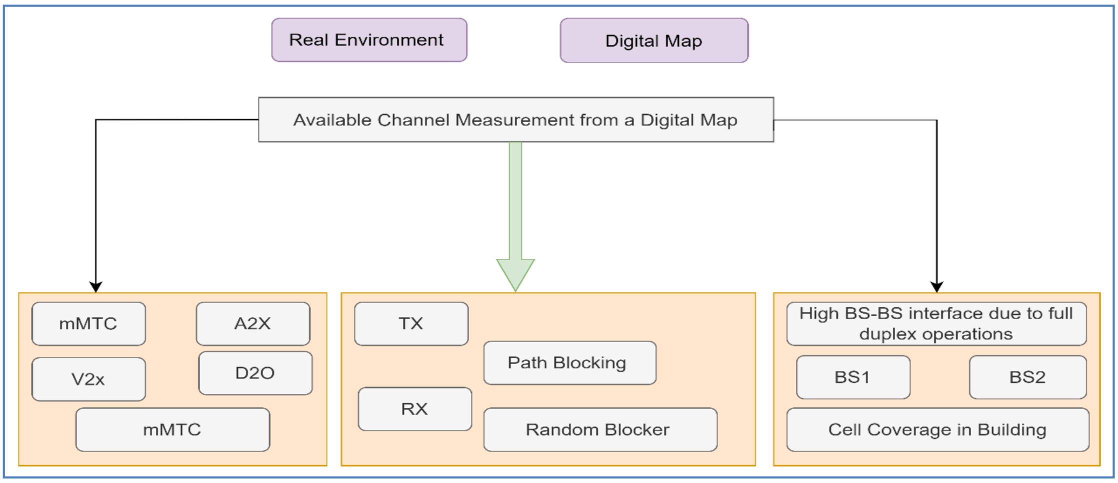



**FIGURE 1.** - **Property-Based Map-Based Model [25]**

### 2.1.5 Broadband mm-wave Massive MIMO Systems with Hybrid Precoding

Future data rates for the Internet of Things (IoT) may be addressed by massive MIMO in the mm-Wave band. For large mm-Wave MIMO systems without considerable cumulative rate loss, hybrid precoding is a practical solution to cut down on the number of radio frequency (RF) chains. Using fictitious narrowband mm-Wave channels and hybrid precoding, current research is appraised. On the other side, hybrid precoding employs phase shifters (PS) with high resolution (HR) and significant pothey r losses. For realistic large-scale, frequency-selective, multi-input, multi-output, broadband mm-Wave systems, an one-bit PS-based energy-efficient hybrid precoding technique has been studied. Cross-entropy optimization (CEO).

### 2.1.6 Common DL Datasets of Massive MIMO Antennas

A Deep MIMO dataset that has been published by researchers is crucial for any study. They offer Massive MIMO antenna design data sets or mm-Wave data sets. A general data collection for mm-wave antennas is provided here. They also provide information in more details about the structure for a typical data set for Massive MIMO antennas. These provide information about the dataset design of the channel.

### 2.1.7 Multiuser Hybrid Beam-forming Based on Learning-Assisted Link Adaptation

To achieve per-user beamforming gain at the base station, this work is depends on hybrid beamforming architecture of the downlink of multiuser millimeter-wave systems, where the number of base station antenna elements is proportional to the users. . distance. This design is based on simulation, and the proposed learning allows for target bit error rate tuning, resulting in significantly higher data rates than typical link tuning based on increasing signal-to-noise ratio thresholds. shown to be obtained.

### 2.1.8 Train Beam Codebook Using Neural Network

Machine-learning is a machine-learning approach for training the green beamforming codebook for massive MIMO systems. It is based on a beam codebook that learns from the user's position and environment, and the neural network design that benefits from hardware constraints. however, the difficulty of code book creation in large-scale MIMo systems has been significantly constrained by the hardware limits of mm-Wave/THz and the utilization of all-analog or hybrid transceiver designs. A single-antenna user can connect to their mm-wave BS (base station) with M antennas in the system model, using supervised learning. Line of sight (LOS) is the first possible situation, and if a user loses her LOS connection, the above indoor scenario will occur. The 68-ray training codebook reaches about 90% of the upper bound, with a 64-ray pattern that can be tuned for size and beam pattern [20-25].

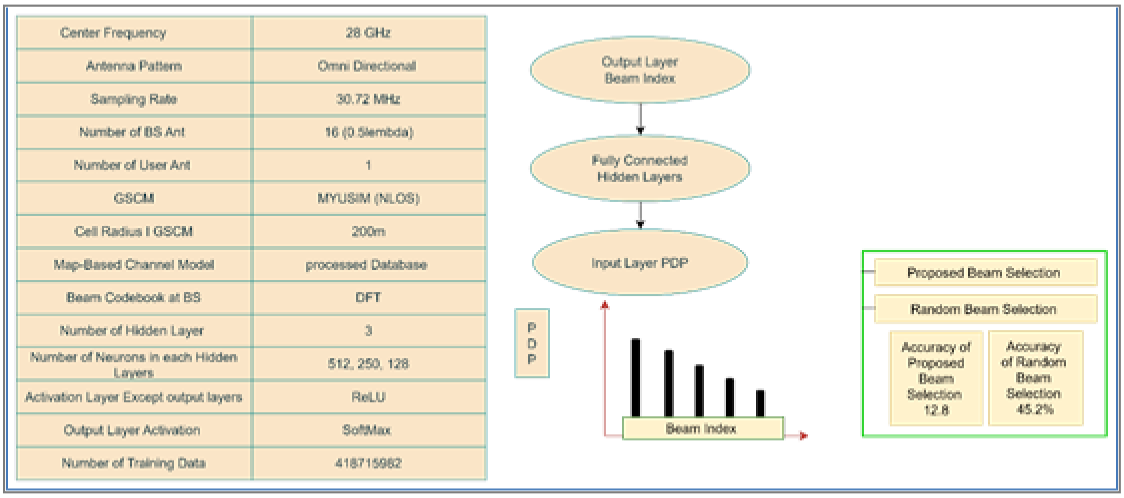



**FIGURE 2. - The perform development for the card-based channels [25]**

### 2.1.9 mm-Wave channel model based on maps

The proposed map-based model enables mapping-based models to be used in SW test benches for various mmWave modeling applications, enabling HW measurements and additional application connectivity types such as D2D, V2X, A2X and models ad hoc cell layouts. A Using a DNN-based beam selection technique, the data set, and the beam selection method and parameter simulations in Part 2 are DNN-based. The proposed approach applies CDF (cumulative distribution function) and GSCM (geometry-based probabilistic channel model). Different models give different results, with PDP (Pothey r Day Profile) accuracy having a high flexibility of 45.2%, and Beam selection algorithm using CDF having a low accuracy of 12.8% [25-28].

### 2.1.10 mm-wave energy traces in the narrowband for network analysis

presented a model to assess ML frameworks for analyzing the protocol layer and pinpointing problems at the physical layer in 60 GHz networks. The major objective is to deliver an ML framework that can precisely identify submitted networks and enable network problem identification. This kind's major emphasis was on millimeter wave and broadband antennas. Essentially, this model is a machine learning framework that makes use of EDHMM and template matching to automatically infer protocol layer information. By examining the variability of channel traces, the major objective was to pinpoint structural components of unexpected behavior. Using directional antennas and a machine learning system, this problem was resolved [29].

### 2.1.11 Recognition of distant gestures with millimeter-wave radar

An extended long-range gesture detection model for human-computer interaction is presented in this work using millimeter-wave radar (HCI). The model employs 3TX and 4RX antennas for detection and is based on the CNN machine learning technique. For model validation, three real-world scenarios they're employed, with the first requiring two participants to stand 2.4 meters away from the radar and make the same four gestures repeatedly for 30 minutes in order to gather 60 gesture data points. The first three gestures' accuracy drastically declined, and it was determined that the external environment had the most impact on the model [29–31].

### 2.1.12 Significant Smart Surfaces Support mmWave Learning from Deep Channels for Massive MIMO Systems

Using MIMO, they provide a DL approach to the channels estimation on LIS in this study MIMO. In order to estimate both direct and cascaded channels, a dual CNN architecture was created. This allowed each user to access his CNN and decide its own channel in multi-user scenarios. It is backed by cutting-edge deep learning-based techniques that compare the effectiveness of suggested deep learning frameworks and produce superior outcomes. Strong estimation performance may be achieved by training deep networks with multi-channel implementations. A different set of test data is produced. Performance during the prediction phase is verified using training data. The suggested deep learning frameworks are outperformed by existing DL-based algorithms [104, 105], which also achieve reasonable channel estimate accuracy. Because of this, the suggested DL approach demonstrated accurate channel estimate that could accommodate user position variations of up to 4 degrees.

### 2.1.13 FDD Massive-MIMO Antennas Selection Using Deep Learning

MIMO systems provide a millimeter-wave radar-based long-range gesture recognition model which is flexible for human-computer interaction (HCI). The model is depending on a DL algorithm called CNN and uses 3TX and 4RX antennas for detection. Three real scenarios are used for model validation, with the first scene requiring two participants to stand 2.4 meters away from the radar and repeat four gestures for 30 minutes to collect 60 gesture data points. The accuracy of the first three gestures decreased significantly and it was concluded that the external environment influenced the model the most [102]. they compared the performance of different antenna selection systems based on DL and conventional selection to find a continuous differentiable function. Our suggested solution outperformed both systems and eliminated significant frequency discrepancies and errors in uplink channel estimate.

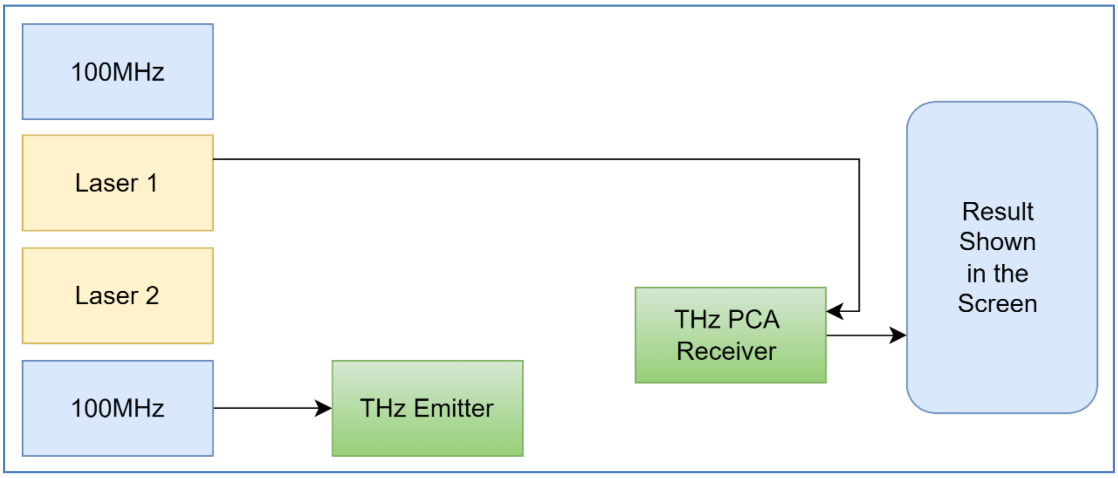



**FIGURE 3. -: Schematic of the TDS THz system [37]**

### 2.1.14 Machine learning using 5G MIMO data

Application of Deep Learning to Beam Selection [114] describes specific dataset of studying vehicle-to-infrastructure beam selection techniques using millimetre waves. To realize the channels presented in the 5G scenario, they introduced the traffic simulation that combines a ray tracing simulator and the vehicular traffic simulator. Designed for enhance functionality a traffic simulator. They utilized a certain dataset. to study the beam selection technique. Several other modeling methods They compared RT (Ray Tracing Simulation) employed in this work with Nyusim and Quadriga [115, 116] utilizing these two programs. RT can generate data that serves two main purposes. RT helped in this scenario by processing the data using various kinds of DL algorithms. Among others, random forests and DNN achieved practically 60% accuracy. The RSU antenna arrays they employed to send and receive data have as their main objective mmWave MIMO. Future improvements to this article should make it more practical and affordable.

## 2.2 ML to A body-centered communications system

Portable body-centric verbal interaction structures have expanded their programs and their locations over the past few inadequate years. These structures are used in many different applications, including those related to healthcare, sports, the military, identification structures, smart phones, etc.

### 2.2.1 THz networks that are body-centric

Wireless communication systems have benefited greatly from terahertz communications. Terahertz communication is hailed as a key enabler. THz has recently proved to be very popular for (in-body) and (on-body) communications. In this model, described methods, channels, modulation techniques, network architecture, and noise modeling for body-centric communication in the THz band. In this paper, they discuss applications of THz sensing and medical imaging. To combat this epidemic, the HF band should be considered. Like the entire global economy, people are affected by COVID-19. Finally, through the design of her body-centric THz applications, she provides insight into the use of her THz spectrum for intra- and supra-body communication. This article covers modeling, modulation, THz band noise, and other topics.

### 2.2.2 Assessment of Human Muscle Mass and Sarcopenia Diagnosis Using a Passive Flexible UWB Myogram Antenna Sensor

Measurement mass of human muscle is the hot topic in the recent antenna field, and researchers have developed a passive, non-invasive, ultra-wideband (UWB), flexible, Myogram antenna sensor of sarcopenia detection. This sensor is used to measure skeletal muscle mass from different muscle sites and to detect metabolic side effects such as diabetes, depression, abnormal cholesterol levels, and weight gain. To assess protein, three methods are used: linear regression of forecast data, dual-energy X-ray absorptiometry, and an NMF filter. The proposed method does not use empirical lean body mass calculations for qualitative assessment, but does allow for a protein score of less than 6 and a score more than 5 to indicate the presence of sarcopenness and severe disease.

### 2.2.3 Non-They arable with respect to privacy Occupancy Monitoring System for Next-Generation Body-Centric Communication Using Wi-Fi Imaging

This application concentrated on a novel Wi-Fi imaging-based, non-portable, device-free occupancy monitoring system for the future intelligent buildings. Future communication networks will be pothey red by wireless and portable devices. In this study, they talked about spotting someone while they are going about their daily business without touching them.

### 2.2.4 Using Wireless Signals, a DL Framework for Subject-Independent Emotion Detection

researchers used a special noise filteringtechnique for collecting most of human heart-beat and respiration signals from the High-Frequency Reflections of the human body. A DL approach is also used to compare the results. According to this article, the wireless emotion recognition device they proposed can also be used with ECG data.

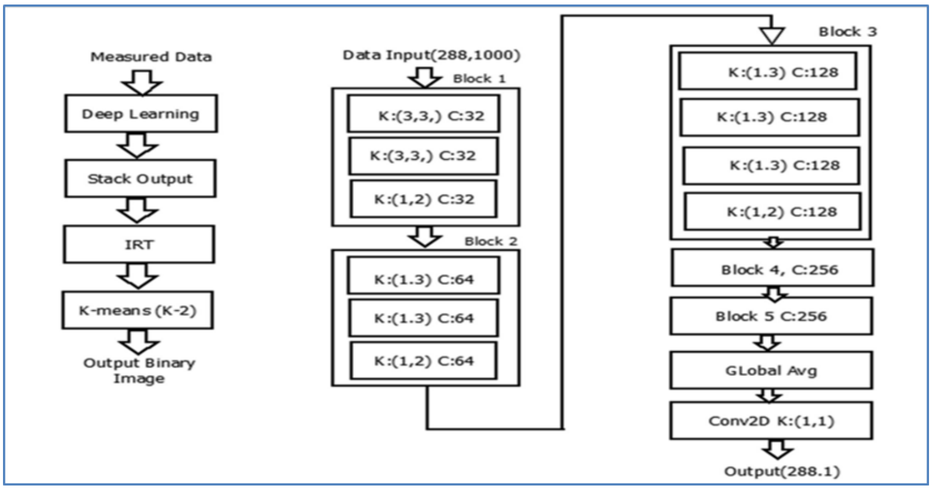



**FIGURE 4. - The THz DL CT model's schematic diagram [37]**

### 2.2.5 Propagation and Antennas to the Bodyentric Communications

The 4G generation of mobile communications will heavily rely on communication centered on the body technologies. A writers discuss where body-centric communication systems are now located. Recent papers [73,74] have extensively discussed antennas for body-centric communication, including button antennas [76–78] and antennas for 10 MHz surface-to-body transmission [75]. The allocation of a system or of a spectrum affects bandwidth. The criteria for radiation patterns are quite difficult to define. Various uses, including medical sensors and medical assistance via implants and cutaneous sensors, are as well obtaining notice. The antenna and propagation of a body-centric communication system are combined in this design.

## 2.3 The THZ communication system, using ML

In spectroscopy, THz frequencies are employed for a number of functions, including the transmission and reception of THz electromagnetic waves. They are crucial for the identification of met materials, the 6G network, the visualization of concealed objects, and beam selection. To overcome attenuation brought on by the THz band's high frequency, hybrid beamforming is essential.

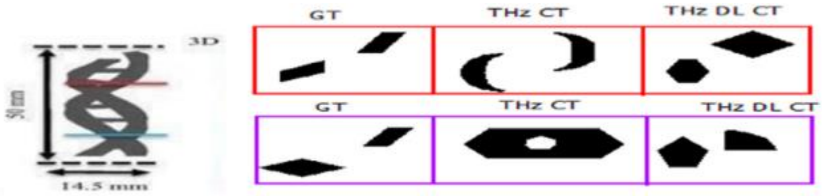
### 2.3.1 DL computed tomography at terahertz

The THz-DL-CT system is a model that can see concealed objects made of different types of materials. Its MSE is 1.86%, that is lower than that of typical THz-CT system. To produce superior pictures at high spatial frequencies, the model could apply kernel filters. This is helpful for viewing the internal structure of 3D objects. Figure (5a, and 5c) displays the end product., demonstrating the model's accuracy.

### 2.3.2 Terahertz system beam selection method with low complexity

The suggested beam selection model makes use of the RFC-based beam selection technique, a ML algorithm, to achieve a better balance between sum-rate and complexity. It takes into account a THz multi-user uplink system with a hybrid beamforming architecture and a thorough approach for determining the maximum total rate. Though it was also employed, the SVM model lacked data bias and the balance of two data sets. This study examines communication problems and a machine learning strategy that will help the 5G communication system be improved.

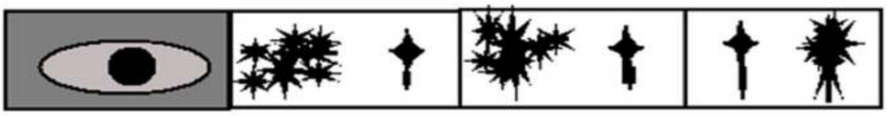
### 2.3.3 Intelligent terahertz met material identification with deep learning security




(a)

| | MSE | SSIM | IOU |
|---|---|---|---|
| THz CT | 0.03496 | 0.9325 | 0.3159 |
| THz DL-CT | 0.01864 | 0.9561 | 0.4601 |

(b)



(c)

**FIGURE 5. - (a) A contrast between THz CT and THz DL-CT. (b) Numerical metrics on two methods; (c) Visible picture and 3D THz images produced by THz DL-CT on a testing item [37]**

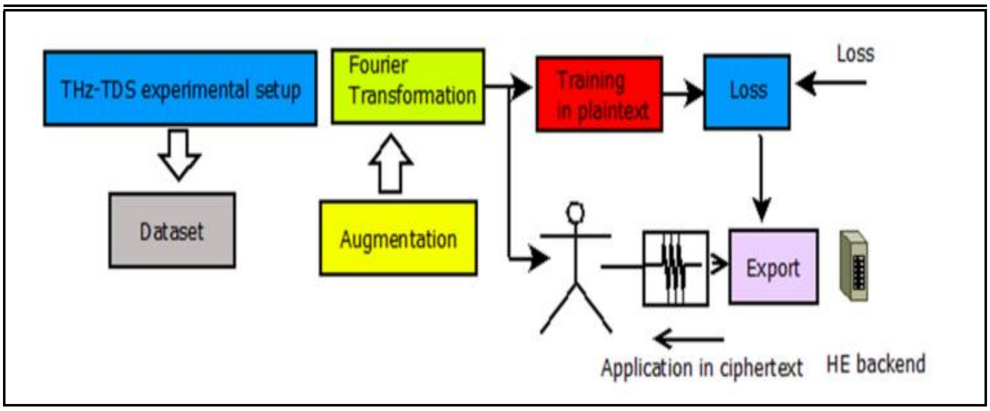



**FIGURE 6. - illustrates the THz metamaterial identification workflow for private preservation [39]**

Thz technology and CNN model are used to detect metamaterials in mixtures. To obtain electromagnetic response signals in THz TDS, a commercial photoconductive antenna and the THz wave is reflected by two lenses. Random augmentation is used to obtain large amounts of data which are translated to the frequency domain. The findings were compared using the SVM algorithm, the human baseline, and CNN. The human baseline had a mean accuracy of 56.97 percent, the SVM technique had an accuracy of 87.9 percent, and CNN had an accuracy on every fold. This paper demonstrated that DL with CNN improves accuracy in detecting certain conditions.

### 2.3.4 6th G Wireless communications: prospective methods and vision

Thz communication (Thz) is a theoretical framework for mobile communication networks that aspires to reduce latency to less than 1 ms, or even zero. To manage massive volumes of data, it employs UM-MIMO and PM-MIMO methods as well as machine learning strategies like categorization or neural networks. To ensure the success of 6G, certain power supply concerns, network security issues, and hardware design issues need to be resolved. Millimeter waves and THzbands must have recreated for use together. If issues can resolve, adaptable.

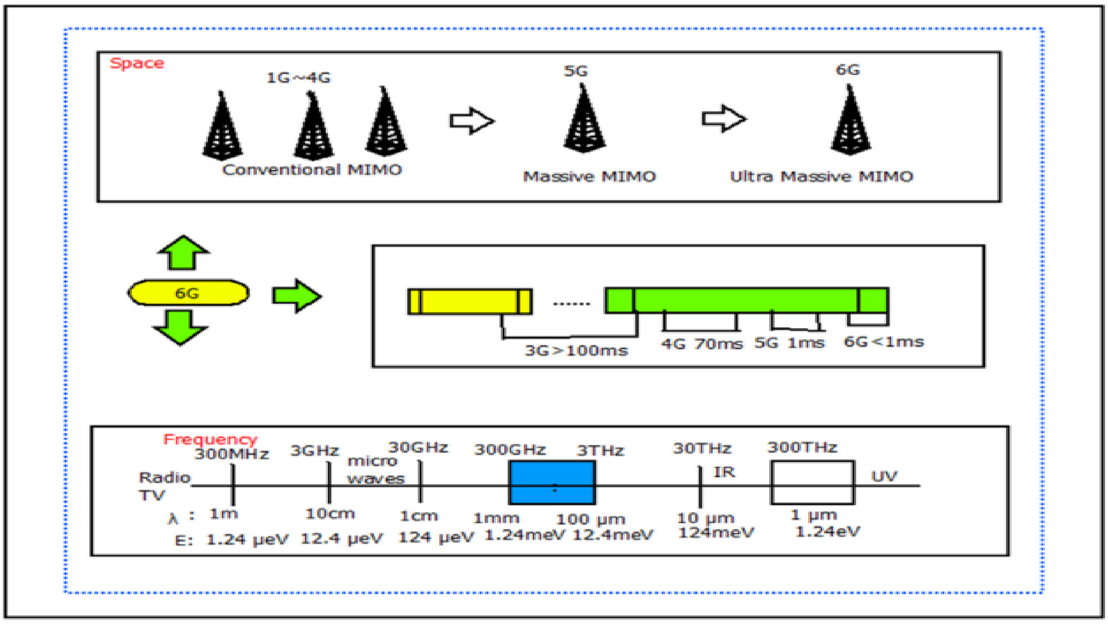



**FIGURE 7. - 6G based on the use of time, frequency, and space resources [40]**

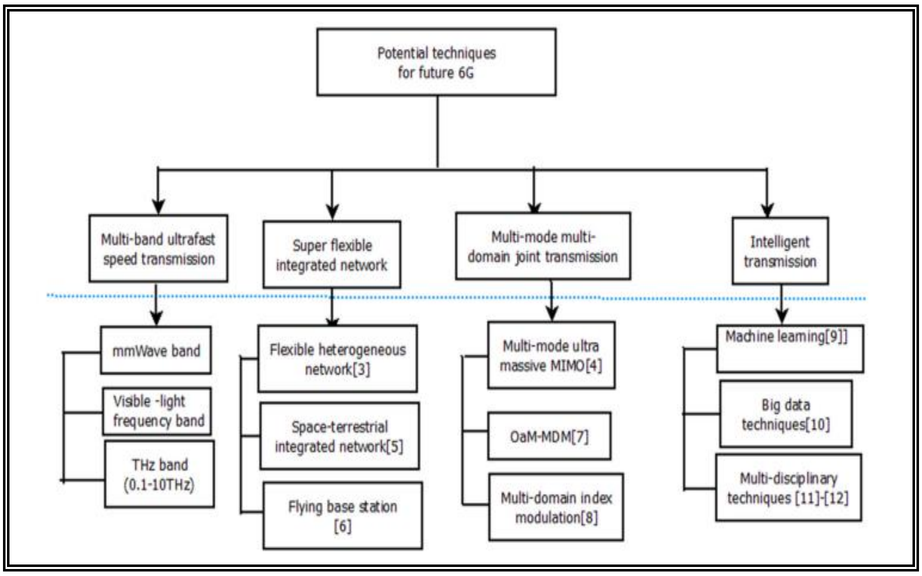



**FIGURE 8. - A few exciting 6G network technologies [40]**

### 2.3.5 Terahertz communications

The term "Thz communications," sometimes known as "sensor communication," refers to a comprehensive and progressive concept of THz communications that also incorporates machine learning and THz antennas. Although the electrical and photonic THz transceiver designs now in use can provide greater power, electronic platforms can. As it could be able to attain a terabit per second data throughput without the use of any extra spectral efficiency augmentation techniques, THz communication is striving to play a significant part in future 6G technology. The advanced technological fields of imaging, localization, and sensing that can be developed utilizing THz technology are discussed in this study. Wireless services in the future are anticipated to be location-based, necessitating machine learning for sizable data sets and artificial intelligence (AI) for map interpolation.

## 2.4 DL and DL design of a satellite antenna

A spacecraft that orbits the Earth is known as a satellite. These satellites provide information to a central station, which produces programs for regional stations that use cables or the airwaves to distribute the information. The following is an explanation of the many uses of machine learning and deep learning for satellites.

### 2.4.1 Cross-polar optimization and design acceleration

SVM, ANN, DBS, and kriging are all machine learning methods used to create and improve reflect array antennas. SVM reduces computing time while improving accuracy, while ANNs improve cross-polar isolation and discrimination. Kriging is used to forecast phase replay and losses. Characterizing the complete matrix of reflection coefficients is done using ANNs. DBS applications use a Moments-based approach using local periodicity (MoM-LP) for analyze a large reflect array. ML algorithms are a promising system for accelerating reflect array research.

### 2.4.2 Hoping beam multibeam satellite system

The most crucial point is that a DL-The generated based path to make practical BH in multi-beam satellite system simpler. This strategy makes use of data-driven paths, learning, and optimization to provide a rapid, almost ideal, and workable BH scheduling solution. In the satellite coverage region, the Beam Hopping (BH) technology provides high level of adaptability to manage temporal fluctuations and erratic traffic demands. A proposed iterative method for BH lighting design makes it challenging to find appropriate BH designs as the search space grows fast. To get the highest deep learning forecast precision, optimization techniques like DL and deep learning can be coupled. This approach shows enhanced BH pattern selection, applicability, and performance improvement.

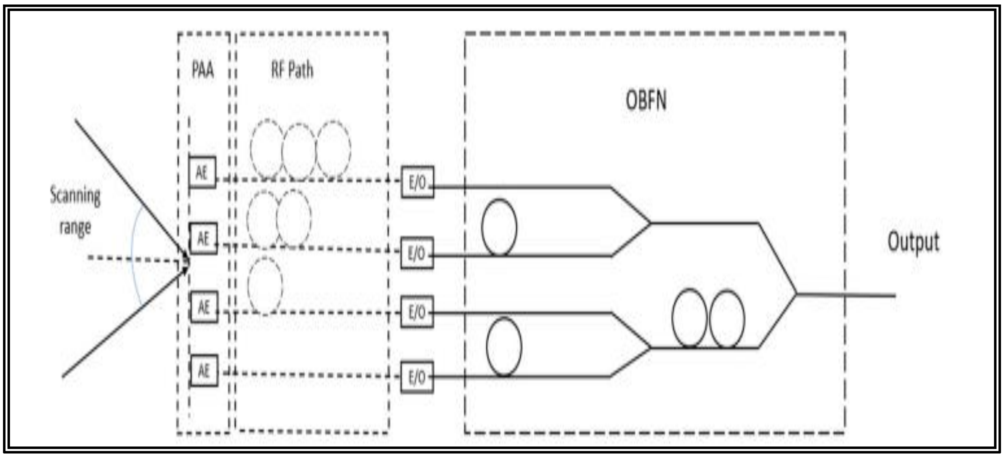



**FIGURE 9. - An optical beamforming network (OBFN), a phased array antenna (PAA) system, and antenna elements (AEs) are a few examples of optical beamforming networks [52]**

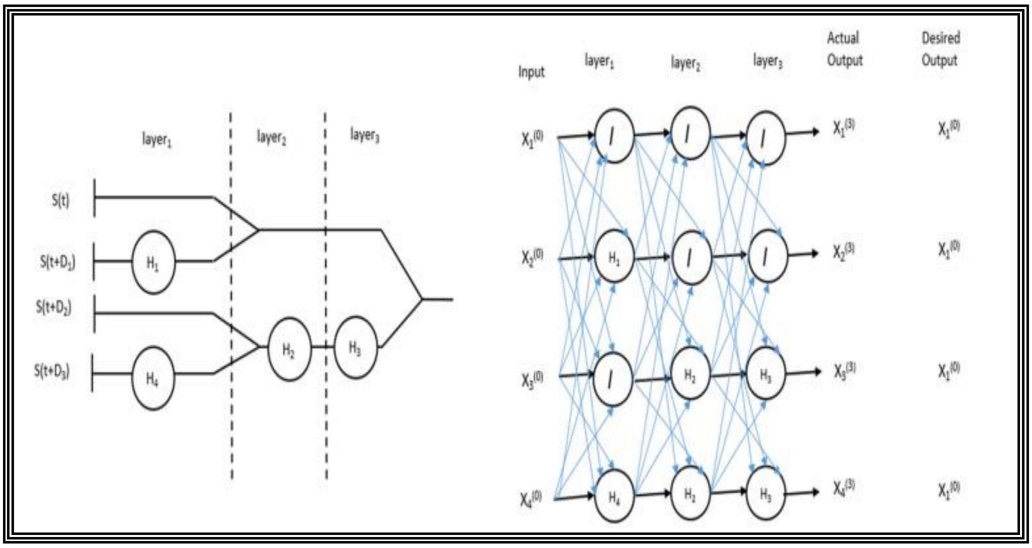



**FIGURE 10. - Its neural network design is shown in the right figure, while the OBFN system (4-1) is shown in the left diagram [52]**

### 2.4.3 optical beamforming networks' tuning

The Phased Array Antenna (PAA) device may be able to pick up signals from some projections, but it has its own disadvantages, such as higher drag force, high maintenance costs, and decreased drag forces. Planes must aim their transmission beams at the satellite in order to broadcast or receive RF signals, and OBFNs must be calibrated before being used for this function. In order to receive the necessary signal from a certain angle while delaying it by predefined delay values as it travels via RF paths, the PAA system uses a beamforming network and an array of antenna elements (AEs). Nugroho et al. and [14] found that the OBFN structure is scalable and has the same antenna needs.

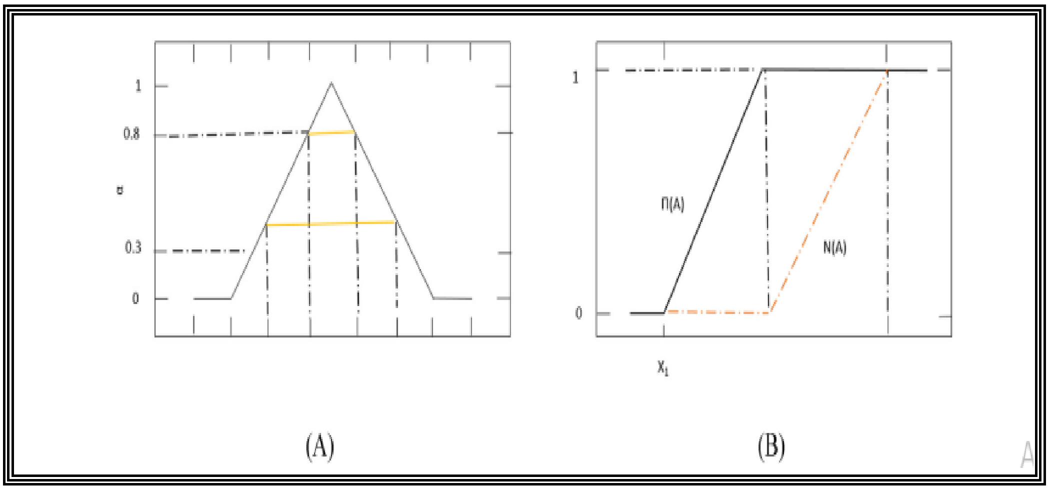



**FIGURE 11. - A triangular probability density function (PD, x), and (B) the related requirement N (dashed) and possibility N (solid) measurements [78]**

### 2.4.4 Tracking mobile devices and positioning antennas in a satellite terrestrial network

In recent years, expanding mobile services have made it challenging for traditional satellite terrestrial networks to function. To reduce the strain on communication, a pointing and tracking method based on artificial intelligence (AI) has been developed for mobile terminals and stations in satellite terrestrial networks. An AI-based self-learning (ASL) network architecture has been created for data sampling and filtering, unsupervised satellite selection, antenna modification methods, and mobile terminal and station tracking. In order to connect with mobile targets, assess the efficiency of mobile communication across satellite terrestrial networks, and open up a new path toward integrative collaboration, artificial intelligence is used.

### 2.4.5 Satellite communication

In areas like flexible payload optimization, beam congestion prediction, interface identification and classification, and anomaly detection, AI may be utilized to automate satellite operations.

## 2.5 ML for the unmanned aerial vehicles

Unmanned Aerial Vehicles (UAVs) and machine learning are essential applications for academic and industrial research. This study focuses on applying machine learning and its approaches to a variety of fields. UAVs are used due to their high resolution, low altitude, flying capabilities, and likelihood, and have potential applications for scientific study.

### 2.5.1 UAV depends on 5G radio access networks

In order to create UAV-based radio access networks, researchers explain why, how, and what kinds of machine learning algorithms perform best in this application. They focused particularly on methods for monitored and rewarded learning. They also talked about radio access networks and focused also be provided with radio access networks based on unmanned aerial vehicles.

### 2.5.2 Localization of construction resources using a UAV-RFID platform

. The UAV application is a data gathering and analysis application that uses k-nearest neighbors machine learning method for classification problem resolution. It is suggested that employing the UAV-RFID platform to find construction supplies is a realistic alternative. Technology and research have limitations in locating construction resources, but due to the better agility of UAV, the limited identifying range of RFID may have been solved by merging UAV with RFID platforms.

### 2.5.3 AI for UAV enabled wireless network

In this paper, the researchers present a detailed description of current study in the field of artificial intelligence-enabled UAV networks. They also discuss some of the limitations of existing research and provide some prospective notions that could be researched in the near future. Also they discussed some of the work done in Florida for UAV-based networks to investigate intelligence deployment at the boundary of UAV networks. Also, they give a detailed introduction to each artificial intelligence problem discussed in this work, which makes it easy for people from different backgrounds to understand. Smart cities and the spread of aerial base stations are two uses of UAVs that offer incentives. The experts looked into how machine learning is used to improve the performance of UAV networks in these situations. They also show how FL techniques are used in UAV networks.

### 2.5.4 Using multispectral imaging and machine learning methods with unmanned aerial vehicles

They thought that each field of winter wheat would have a different amount of grain and protein. For farming to be profitable, you need to be able to predict how much and what kind of crops will grow. Commercialization has made it possible for UAVs to use low-cost multispectral cameras, and improvements in machine learning techniques have made it possible for UAVs to make better predictions. Spectral absorption and plant height are used to predict how much wheat grain will grow and how much protein it will have. In this study, they looked at how well machine learning based on absorption and traditional linear regression models could predict wheat grain yield and protein content.

### 2.5.5 Convolutional neural networks are used to the count cattle and detect in UAV photos

The authors of this study proposed a technique for identifying and counting animals using UAV pictures. It's rare for targets to seem to be the same size in UAV images. Additionally, applying the principle of domain adaptation might help a bit different dataset perform better. Detection and counting tools for cattle can also be used to find and count other slow-moving animals.

## 2.6 Machine learning for communication tools in the textile industry

Textiles are used to make these antennas. The development of wireless electronic textiles depends on these antennas. It makes it easier for clothing, sensors, and external devices to communicate. The following publications discuss flexible, washable wearable antennas. The textile system's adaptability is increased through the use of sensors and processes.

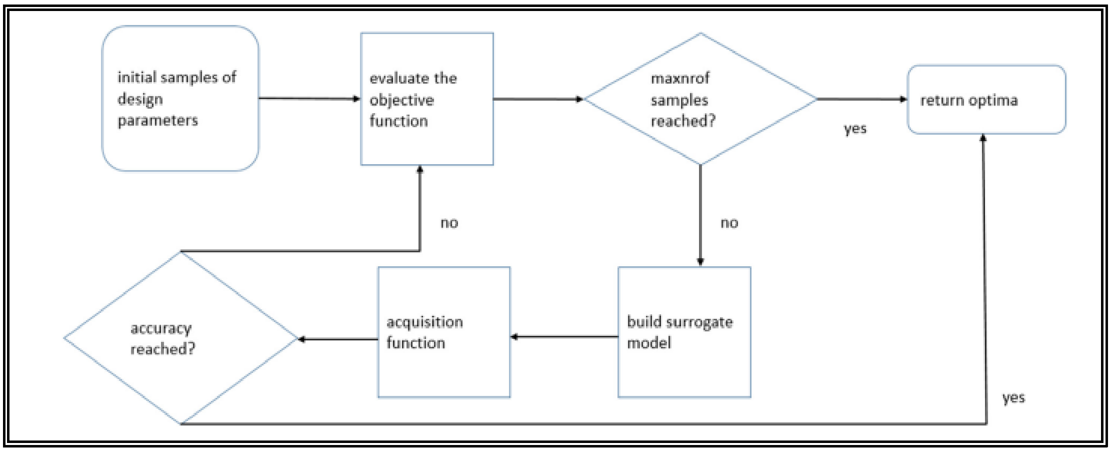



**FIGURE 12. - Diagram of the BO algorithm, [78]**

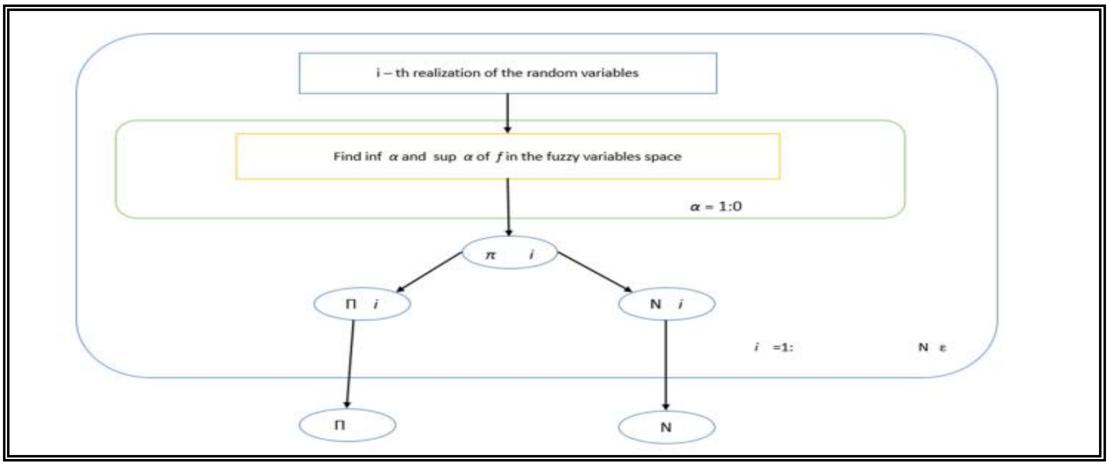



**FIGURE 13.** - **hybrid algorithm being proposed [78]**

### 2.6.1 Hybrid random-fuzzy modeling approach for antenna design based on machine learning

UQ (uncertainty quantification) is a mixed-machine learning method used to transmit aleatory and epistemic uncertainty in antenna design. It is based on statistical methodologies and is used in textiles to design some complicated scenarios. UQ is a real-valued measure that is shown by a PD (Possible Distribution) (x), which can be rectangular or triangular. People often use PDs to show "total ignorance," where x is the cognitive variable. BO (Bayesian Optimization) and the PC growth method are both ways to use machines to learn, which improves the standard of hybrid algorithms and increased accuracy and computational efficiency [79-80].

### 2.6.2 The use of knitted antennas and RFID tags linked by induction for wearable uses

This study made and tested a knitted folded dipole antenna that is connected to an RFID chip through induction. RFID (radio-frequency identification) technology was found to use low-power radio waves to collect data and automatically identify products, while the backscattered power (RSSI) sent by a passive RFID tag can be used to measure material deformations in traditional metal-based tags. The wearable stain sensor needs to be comfortable, stretchy, have a good match between the chip and antenna's impedance, and be able to send and receive signals at different amounts of physical deformation. SVM and Gaussian filters are two ways to use machine learning to look at data. The goal of this system was to track body movements, so RFID tags were attached to knitted antennae that were sewn into the host clothing.

### 2.6.3 Cloth-Face: a battery-less RFID-Based textile platform for handwriting recognition

Based on UHF-RFID, it is a prototype of Cloth-Face technology for handwriting recognition that is built into cotton cloth. This was done with the help of fabric antennas and a 10x10 grid of RFID ICs (integrated circuits) with their own codes. Human-machine interaction always requires touch or body movement, and the most popular on-body interfaces, like trackpads and tapping buttons [86, 87, 88, 89], are often built around the arm to recognize hand movement. Skin electronics [90] are a new idea for a bendable technology that can recognize touch and gestures on the body. This project builds on [91], which showed a simple prototype of ClothFace technology, which is a platform for writing on textiles that doesn't need batteries. The new work will be a real-time recognition system that will be tested in the real world. It can figure out any number from 0 to 9, and thanks to machine learning techniques, it can also do complicated things. CNN is a machine learning method that can be used to recognize images. In tests, the error rates went from 0.23 to 1.7. (Convolutional Neural Network). With this technology, the clothes and fabrics we wear every day can be turned into high-tech user experiences. It can help the person improve how well they can recognize characters.

### 2.6.4 Surrogate-based filling optimization is used to solve electromagnetic problems

Surrogate-Based Optimization (SBO) approaches are looked at in depth. This study was mostly about using several SBO methods for data-driven approximation. The SVM and the Gaussian Process are two types of proxy models. (GP). In general, SBO makes a link between the input parameters and the output parameters.

**Table 2. - The different machine learning methods used in the papers that were looked at for Millimeter Wave [78]**

| Reference No. | antenna used | Algorithm | comparison to | Result |
|---|---|---|---|---|
| [1] | MIMO antenna | reinforecment learning (RL) | Brute-force search | reduction in the number of iterations required to locate the most suitable beamformers and digital precoders for transmission ,with out compromi ipper bound data rate reached through brute -force search |
| [7] | millimeter wave antenna | random forest | naïve-bayes,Adaboost ,RBF-svm and Gradient Boosting | the result suggest that given perfect assumptions , we may get up to 86 p alignment probability |
| [8] | MIMO antenna | alignment method with partial beams using ML(Ampbml) | multi-path decomposition and recovry ,as well as adaptive compresed sensing and hierarchical search | in terms of total training time slots and spectral eefficiency ,the AMPBM outperforms existing methods such as adaptive compressed sensing ,hierarchical seach ,and multi -path decompostion and recovery. |
| [12] | MIMO antenna | deep learning based hybrid precoding method | hybrid precoding schemes | the result is minimiztion of the bit error ratio and enhanced spectrum fea of the mm Wave massive MIMO with low computational complextiy |
| [18] | MIMO antenna | ray -tracing data | | the dataset can be used in deep learning application |
| [19] | hybrid beamforming | KNN | deep learning | the dataset can be used in deep learning application |
| [20] | M antenna LOS | | developed a machine learning - based framework for learning the surroundings and beamforming codebooks that are hardware resposive | |
| [25] | large array antenna | beam selection | | map based millimeter ware channel model |
| [29] | misaligened antenna | EM | | developing channel traces |
| [102] | antenna (3tx,4Rx) | R-D,FFt | | mmwave sensing is used to create a long range gesture recogntion mode |
| [103] | MIMO antenna | deep learning | state of the art Dl based techniques | the exisiting DL based techniques [104,105] are outperformed by the pr deep learning framework and achive reasonable channel evaluation accu |
| [106] | MIMO antenna | deep learning and problemisic sampling framework | ULA | the massive MIMO channel extrapolation algorithm is effective |
| [114] | RSU | random forest ,deep neural network | svm ,decision tree, Ad boost | the result gives about 63% accuracy and it is a very convenient techniqu |

Because of this, other improvement methods move along faster. A nonconductive cloth substrate is used to make textile antennas. With the SUMO (Surrogate modeling) software, the inverse problem of textile antennas is solved. The SBO toolkit is part of the SUMO toolbox. It is based on the EI (Expected Improvement) measure. SVM is a machine learning technique that they used to solve the EM problem. SVM makes it easier to compare generated and measured data.

## 2.7 Machine learning and deep learning for antenna design in global positioning systems

Global Positioning System (GPS) was created for both military and civil use in order to determine geographic locations with accuracy. We can determine how far away a user is from a satellite thanks to data transfer via satellites in Earth orbit. Below are some examples of how deep learning and machine learning are used for GPS in a range of scenarios.

### 2.7.1 An ML method for estimating GPS code phase in multipath scenarios

The NN-based DLL (NN) dependent delay locked loop (DLL) is used to reduce multipath interference in GPS devices. It has lower code phase root mean squared errors than the three standard models in situations with a lot of multipath interference, but it doesn't deal with multipath interference. Multipath signals change the autocorrelation functions of the phase locked loops and the delay locked loops in GPS receivers. This makes it possible to predict the carrier phase and create biases in the code. There are ways to reduce the effects of multipath. These solutions can be put into two groups: signal processing methods and antenna techniques. In [93], a NN-based DLL was made to help with multipath location by focusing on the autocorrelation function when evaluating the receiver. The NN is trained with a model of statistical distribution, and it works best with samples that are evenly spread. The suggested way is more effective than the usual E-L DLL and sometimes does better than the usual solution [94].

### 2.7.2 GPS spoofing detection on unmanned aerial platforms

Unmanned aerial system have piqued the interest of many civil and military software products (UAS). An ML method for detecting GPS proposed.

**Table 3. - compares the various machine learning algorithms utilized in the articles studied for body centric [34,35]**

| Reference No. | Antenna Used | Algorithms Used | compared | Result |
|---|---|---|---|---|
| [32] | THz antennas | Supervised algorithms | | Use of THz based for body – centric networks |
| [33] | UWB | Linear regression | | Absorption of electromagnetic by muscle tissues under near-field circomstances |
| [34] | Planer antenna | K-nearest algorithm,support vector machine | Linear regression | The system was built with off-the shelf ,non-wearable components |
| [35] | TX antenna and RX antenna | Classical machine learning | Deep learning | In comparison to other methods, using a wireless signal for standby emotion detection is a better option |
| [36] | Conventional antenna | ML | | Current postion of the body-centric communication networks |

NN is a machine learning method that uses artificial neural networks (NN) to look at real or fake GPS data and decide whether an attack is happening or not. Unmanned Aerial System (UAS) uses a number of technologies to work, such as the Global Positioning System (GPS), which can be used to track and navigate with an accuracy of up to 3 m. Four satellites send messages to GPS receivers, which pick them up. Cyberattacks, such as GPS spoofing, can happen through these GPS devices. An algorithm has been made for this technology to find this kind of attack. The study's data show that there is a low chance of false alarms and a high chance of finding something [96–100].

### 2.7.3 Putting GPS in second place in a reliable low-power 5G positioning system

This paper investigates the energy consumption of a Deep Learning (DL) dependent millimeter wave (mmWave) positioning solution for mobile devices. It is compared to modern and accurate outdoor positioning systems. The proposed technology decreases the energy required for precise pointing in mmWaves networks and creates an unequal level of perfection in the appearance of non-Line-of-Sight (NLOS) objects. The accuracy and feasibility of the system are compared to existing GNSS-based systems.

## 3. Analysis

Machine learning is a powerful tool for antenna design, but it is not always the best option. To ensure the success of an algorithm, datasets must be validated before using it. Due to the data needs for normalization and feature selection, preprocessing data is challenging, and huge datasets take a long time. The results of Monte Carlo simulations used to examine the performance gap between the suggested design and the conventional design in the field of machine learning revealed that the desired or required BER was set at 103. This suggests that the suggested learning-assisted adaptation easily meets the requisite BER while offering a significantly greater data throughput compared to conventional link adaption based on SNR threshold values. In response, the mean data throughput of a multi-antenna wireless system utilizing hybrid beam-forming in the millimeter wave frequency range was improved using the

Reinforcement Learning (RL) approach. This RL-based strategy requires only a fraction of the repetitions, compared to the comparing brute for the solution [26].

**Table 4. - compares the various machine learning methods applied in the publications under consideration for THz [78,79]**

| Reference No. | Antenna Used | Algorithm Used | Compared to | Result |
|---|---|---|---|---|
| [37] | PCA | THz DL-CT | THz,CT | It shows much superior image quality |
| [38] | Na,Nb,Nr | RFC | SVM | Reduce the computational complexity hybrid beamforming |
| [39] | Photoenductive | CNN | SVM | Developing identification of metamaterials in mixtures |
| [40] | Multi-mode multiple antenna | DNN | | Demo of 6G mobile network |
| [41] | UM-MIMO | DNN | Plasmonic antenna PCA | Future vision of THz communication |

**Table 5. - compares the various machine learning methods applied in the Satellite publications under consideration [46,52,65]**

| Reference NO. | Antenna Used | Algorithm Used | Compared to | Result |
|---|---|---|---|---|
| [46] | Reflect arrays | SVM | MOM-ip | Acoelerate computing time wiout comprmising |
| [47] | Multibeam antenna (MBA) | Brach and bound (BAB) and simples algorithms (SA) are examples of DL-based optimization (DBO) algorithms | Typical data –driven strategied and traditional iterative optimization approaches | The optimization component can ensure the solution efficiency and increase overall performance while speeding up the method of BH pattern selection and allocation |
| [52] | Phased array antenna (PAAS) | Deep neural network | Non-linear programming | Large scale can br tuned for any desired delay |
| [65] | Satellite antennas | Reinforcement learning (RL) algorithms | Traditional satellite – terrestrial networks | Ascertain that our mobile stations and terminals receive the best antenna signal and are subjected to the least amount of communication interfenence from other stations or terminals |

**Table 6. - compares the various machine learning methods applied to the UAV research articles**

| Reference NO. | Antenna Used | Algorithm Used | Compared to | Result |
|---|---|---|---|---|
| [72] | Planer | K-neural networks | Support vecter machines | Synthesize the research on unmanned arial vehicles (UAVs) based on a machine learning environment |
| [73] | Conventional | Reinforcement learning | | Why, how and which of types of algorithms are used in U-RANS |
| [74] | reflectarrays | k-nearest algorithms | | Location as a |

| | | | | |
|---|---|---|---|---|
| | | | | classification problem by using machine learning |
| [75] | Mimo antenna | Artificial intelligence | | Get a detailed overview of the AI's potential application in UAV-based networks |
| [76] | Plannar | Linear regression | | Grain yield and protein content are predicted |

The several iterations required to guarantee data security and accurate data collecting are the most crucial information in this work. The disturbing qualities of GPS include its inaccuracy, frequency of position updates, and penetration rate. An alignment approach with partial beams using Machine Learning (AMPBML) without any prior knowledge is offered, along with a multi-input multi-output system for beam alignment using millimeter wave (mmWave) by many users. Clear data for testing and training continue to be a challenge [32].

The implementation of a hybrid pre-coding technique based on Deep Neural Networks (DNN) takes time and requires a significant amount of time and resources. The proposed method is based for feasible frequency-selective wideband mmWave huge MIMO systems, using one-bit PSs. Additionally, CEO optimization is created to increase the system's earnable sum rate. However, a system is susceptible to errors, which can lead to severe consequences [39,41].

The majority of COVID-19 detection methods now in use use PCR assays. On the other hand, researchers are looking for profitable alternatives. In addition to COVID19 detection, attention is being paid to antibody testing that can differentiate a person who has already been infected, resulting in a better comprehension of the virus's dissemination. THz technology can support patients' remote operations during a pandemic and is used in imaging to identify viruses. For instance, THz-based implantable sensors or sensors on the patient's body can instantly acquire health data and transmit it to healthcare support professionals, who can then act remotely to aid patients. A new technology will alwaysdraws both positive and negative responses. Currently, 5G technology is the major emphasis, and a sizable portion of respondents think 5G technology is bad for human health [57].

Future Although THz communication will be extremely versatile, it will also become very cost-effective since they require 6G networks and other technologies. Support Vector Machines (SVMs), a machine learning technique, were used to design and improve reflect array antennas [89]. Thus, computation time is decreased while accuracy is kept. The main takeaway from [89] is that SVMs can enhance cross-polar isolation and discrimination while maintaining a consistent computation time. however, there is an issue with inadequate infrastructure and resources, as they as a lack of high-quality data. Large datasets have a negative impact on SVM performance because of the longer processing times.

In multibeam satellite systems, practicable BH has been made easier with the use of a Deep Learning (DL)-based technique in [90]. When it comes to the satellite coverage region, BH can maintain flexibility to accommodate erratic traffic demands and changes in time. A rapid, almost ideal, and workable BH scheduling solution was created using a learning and optimization technique. But these are certain problem with DL. The developed procedure time-consuming, expensive computationally, and necessitates a large volume of clean data.

**Table 7.- compares the various machine learning methods applied to the textile-related research articles**

| Reference No. | Antenna Used | Algorithm used | Compared to | Result |
|---|---|---|---|---|
| [78] | Dual –polarized textile patch antenna | PDF | | Hybrid machine learning –based framework |
| [81] | Folded dipole antenna | SVM | | Knitted folded dipole antenna design and application |
| [85] | Dipole antenna | CNN | CNN | Cloth face technology that can recognize handwriting |
| [92] | Textile antenna | Sumo toolbox | | Overview of SBO |

**Table 8.- compares the various machine learning methods used to GPS in the articles under consideration**

| Reference No | Antenna used | Algorithm used | Compared to | result |
|---|---|---|---|---|
| [93] | GPS antenna | Neural network (NN) | Conventional early-minus-late DLL, narrow correlator, and high resolution | In high multipath situations, NN-based DLL generats lower code phase root mean |

| | | | | |
|---|---|---|---|---|
| | | | correlator | squared error than the three traditional approaches (standard early-minus-late DLL,narrow correlator , and high resolution correlator) |
| [95] | GPS SMA antenna | Neural network | Support vector machine and crowd-GPS-see | It has a high likehood of detection and a low likelihood of false alert |

The most important details of the phrases UAV, UAVs, model, and stations are the development of a deep neural network model for tuning Optical Beamforming Networks (OBFNs), an artificial intelligence (AI)-based pointing and tracking method for mobile terminals and stations in satellite terrestrial networks, and the application of AI in satellite communication. Deep RL is used to dynamically modify the speed of the UAV cloudlet (s) to optimize user performance, and machine learning tools are often used to solve problems that could be solved in a more simple and deterministic manner. The National Design for Natural Language Processing (NNDL) is a machine learning technique that can be used to identify and classify animals based on their skin and body shape. The NNDL simulation result is compared to traditional code phase tracking systems such as E-L DLL, HRC, and narrow correlator. A Deep Learning (DL) approach for identifying GPS spoofing signals based on an artificial neural network may encounter several issues, such as high mistake susceptibility and a lack of qualified resources. However, there are several restrictions that require monitoring, cost, and upkeep, and this study has no practical application [95-115]. Tables (3 - 9)

## 4. Conclusion

To sum up, this study has investigated the applications of ML, DL, and AI in the antenna design. The authors have explored different antenna configurations and discovered that using these new technologies can lead to better outcomes compared to traditional methods. The study has focused on different types of antennas, such as THz, UAV, GPS, millimeter wave, satellite, body centric, and textile. The results indicate that ML, DL, AI can reduce simulation requirements, predict antenna behavior, and save time while maintaining high accuracy. The authors have made significant contributions to this study, and there are no financial conflicts of interest. Overall, this study provides valuable insights into the potential of these new technologies in the field of antenna design.

## ACKNOWLEDGEMENT

I extend my thanks and gratitude to my professors, especially Dr. Oras, Dr. Hazem, Dr. Mahmoud and Dr. Ali for their efforts with me in completing this research.

## FUNDING

No funding received for this work

## CONFLICTS OF INTEREST

The authors declare no conflict of interest

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