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Design and development of microstrip patch antennas for the new technologies

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Prophetic Hadith

"Everything has a reality, and until the servant realises that what harmed him could never have missed him and that what missed him could never have harmed him, he will not be able to experience the reality of faith."

– Prophet Muhammad (PBUH)

Dedication

I dedicate this thesis to my dear parents, for their unconditional love and constant prayers. To my siblings, for their constant support and trust. To my teachers, whose knowledge and guidance have been a significant influence on my journey. To my friends, who have eased my burdens along the way. And to everyone who has supported me, publicly or silently. From the bottom of my heart, I say: Thank you.

– *Degachi Riadh*

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All, gratitude is due to 'ALLAH' for giving me the strength, courage, and commitment that enabled me to start and finish this work.

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– *Degachi Riadh*

Abstract

This thesis investigates the use of machine learning models (ML) to optimise the design of microstrip patch antennas, which are essential in modern communication systems. While microstrip antennas are widely used due to their compact and lightweight properties, their performance depends on accurate design, traditionally requiring iterative methods. In this work, the focus is placed on a microstrip antenna operating at 2.45 GHz, a widely adopted frequency within the ISM band due to its extensive use in Wi-Fi, Bluetooth, RFID, and IoT applications. This study aims to accelerate and improve antenna design by employing machine learning techniques to predict antenna dimensions based on performance metrics, such as return loss, gain, and radiation pattern. The research looks at different microstrip antenna technologies, including how they are fed and analysed, and examines various machine learning methods like Random Forest, Support Vector Regression (SVR), Decision Trees, and Artificial Neural Networks (ANN). The models' performance is assessed using error metrics like Mean Squared Error (MSE) and Mean Absolute Error (MAE). Results demonstrate that machine learning models, particularly Random Forest and ANN, outperform traditional methods in predicting antenna dimensions. Moreover, the application of ML led to a noticeable improvement in antenna performance, achieving an enhancement of the return loss (S11) from –25 dB to –30 dB. This research highlights the potential of ML to enhance antenna design efficiency, reduce design time and cost, and offer a foundation for future studies in antenna optimisation.

Keywords: Artificial Neural Networks, Decision tree, Machine Learning, Patch Antenna, Random Forest, Support Vector Regression.

Résumé

Cette thèse étudie l'utilisation des modèles d'apprentissage automatique (ML) pour optimiser la conception des antennes micro-ruban, qui sont essentielles dans les systèmes de communication modernes. Bien que les antennes micro-ruban soient largement utilisées en raison de leur compacité et de leur légèreté, leurs performances dépendent d'une conception précise, nécessitant traditionnellement des méthodes itératives. Dans ce travail, l'accent est mis sur une antenne micro-ruban fonctionnant à 2,45 GHz, une fréquence largement adoptée dans la bande ISM en raison de son utilisation étendue dans le Wi-Fi, le Bluetooth, la RFID et les applications IoT. Cette étude vise à accélérer et à améliorer la conception des antennes en employant des techniques d'apprentissage automatique pour prédire les dimensions de l'antenne à partir de paramètres de performance tels que le coefficient de réflexion, le gain et le diagramme de rayonnement. La recherche examine différentes technologies d'antennes micro-ruban, y compris leurs méthodes d'alimentation et d'analyse, et évalue divers modèles d'apprentissage automatique tels que la Forêt Aléatoire, la Régression par Vecteurs de Support (SVR), les Arbres de Décision et les Réseaux de Neurones Artificiels (ANN). Les performances des modèles sont évaluées à l'aide de métriques d'erreur telles que l'Erreur Quadratique Moyenne (MSE) et l'Erreur Absolue Moyenne (MAE). Les résultats démontrent que les modèles d'apprentissage automatique, en particulier la Forêt Aléatoire et les ANN, surpassent les méthodes traditionnelles pour prédire les dimensions des antennes. Cette recherche met en évidence le potentiel de l'apprentissage automatique pour améliorer l'efficacité de la conception des antennes, réduire le temps et le coût de conception, et fournir une base pour de futures études en optimisation d'antennes.

mots-clés: Réseaux de neurones artificiels, arbre de décision, apprentissage automatique, antenne patch, forêt aléatoire, régression à vecteur de support.

الملخص

تبحث هذه الأطروحة في استخدام نماذج التعلم الآلي (ML) لتحسين تصميم هوائيات الرقعة الميكروية، والتي تعد عنصرًا أساسيًا في أنظمة الاتصالات الحديثة. وعلى الرغم من أن هذه الهوائيات واسعة الاستخدام بفضل حجمها الصغير وخفة وزنها، إلا أن أدائها يعتمد على دقة التصميم، والذي يتطلب تقليديًا طرقًا تكرارية. في هذا العمل، يتركز الاهتمام على هوائي ميكروي يعمل عند التردد 2.45 غيغاهرتز، وهو تردد شائع الاستخدام ضمن نطاق ISM نظرًا لاعتماده الواسع في تقنيات Wi-Fi وBluetooth وRFID وIoT. تهدف هذه الدراسة إلى تسريع وتحسين عملية تصميم الهوائي باستخدام تقنيات التعلم الآلي للتنبؤ بأبعاد الهوائي بناءً على معايير الأداء مثل معامل الانعكاس، والكسب، ونمط الإشعاع. كما تستعرض هذه الأطروحة مختلف تقنيات الهوائيات الميكروية، بما في ذلك طرق التغذية والتحليل، وتختبر عدة خوارزميات للتعلم الآلي مثل الغابات العشوائية (Random Forest) وآلة المتجهات الداعمة (SVR) وأشجار القرار والشبكات العصبية الاصطناعية (ANN). وقد تم تقييم أداء النماذج باستخدام مقاييس الخطأ مثل متوسط مربع الخطأ (MSE) ومتوسط الخطأ المطلق (MAE). أظهرت النتائج أن نماذج التعلم الآلي، وخاصة الغابات العشوائية والشبكات العصبية الاصطناعية، تتفوق على الطرق التقليدية في التنبؤ بأبعاد الهوائي. علاوة على ذلك، أدى تطبيق الذكاء الاصطناعي إلى تحسين ملحوظ في أداء الهوائي، حيث تم تحسين معامل الانعكاس (S11) من 25dB- إلى 30dB-. وتبرز هذه الدراسة الإمكانات الكبيرة للتعلم الآلي في تعزيز كفاءة تصميم الهوائيات، وتقليص زمن وتكلفة التصميم، وتوفير قاعدة صلبة لدراسات مستقبلية في مجال تحسين الهوائيات.

الكلمات المفتاحيّة: الشبكات العصبية الاصطناعية، شجرة القرار، التعلم الآلي، هوائي التصحيح، الغابة العشوائية، الانحدار المتجهي الداعم.

List of Scientific Activities

Journal Publications

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International Conferences

1) Riadh DEGACHI, Said GHENDIR. "Design and Simulation of U-slotted Microstrip Patch Antenna for L, S, C and X Band". *The 1st International Conference on Advances in Electronics (ICAECCT'23)*, 25-26 Oct 2023. Mascara, ALGERIA. *Presented.*

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CHAPTER 1

Introduction

1 Background

British physicist James Maxwell established the groundwork for a comprehensive theory of electromagnetism in 1864 by predicting the existence of electromagnetic (EM) waves and developing Maxwell's equations [1]. Later, German physicist Heinrich Hertz experimentally verified the presence of these EM waves. EM waves are a form of energy that propagates through space as oscillating electric and magnetic fields [2]. Since they can convey data over enormous distances without needing physical connections, these waves are essential to wireless communication. Due to their frequency or wavelength, electromagnetic waves can be categorised into radio waves, infrared, microwaves, ultraviolet, visible light, gamma rays, and X-rays [3]. Wireless communication, which involves sending speech, video, and data over a network without physical connections between transmitters and receivers, is one of the most vital uses of electromagnetic waves. Wireless communication is becoming increasingly common, partly because of the ease, portability, and adaptability of electromagnetic waves. Today, wireless communication systems encompass various technologies, including cellular networks, Wi-Fi, Bluetooth, and satellite communication, all of which operate at different frequencies and use diverse modulation techniques to transmit data efficiently and securely. As the interface between electronic circuits and electromagnetic waves for signal transmission and reception, antennas are essential components of these systems. The antenna itself, a transmission line, and a transceiver often make up an antenna system. An alternating current (AC) signal carrying information is sent by the transmitter along the transmission line, where it is transformed into an electromagnetic field and sent out into free space by the transmitting antenna. Then, like travelling waves, these electromagnetic waves propagate in all directions. At the receiving antenna, the travel wave is captured, converted back into an AC signal, and processed by the receiving terminal. Antennas are responsible for signal converting throughout this process; they change the transmission line signals into electromagnetic waves for unlimited propagation and then back into AC signals for processing at the receiving end.

To be able to radiate or receive electromagnetic (EM) signals, antenna design essentially entails changing their form, transforming alternating current (AC) on the transmission line into EM waves in space. In other words, even small modifications in the geometry of an antenna can significantly affect the propagation and radiation pattern of EM signals. For example, in wireless communication, receiving antennas might be placed in different spatial orientations and are frequently situated far from transmitting antennas. Nevertheless, an antenna's omnidirectional radiation pattern does not necessarily meet the needs of real-world wireless communication applications.

Antenna modelling involves developing a mathematical representation of the antenna's behaviour. The antenna's performance can be simulated using this model in a variety of scenarios, including those involving varying frequencies, polarisations, and environmental influences. As a result, antenna modelling is a critical step in the design and development processes, enabling optimisation to meet the desired specifications.

Electromagnetic (EM) simulation is essential and reliable in antenna modelling, enabling an accurate assessment of antenna performance under diverse conditions. Through EM simulation, key electromagnetic properties such as radiation patterns, gain, and impedance can be determined. Additionally, EM simulation tools offer graphical results that highlight the relationship between antenna performance and factors like shape, size, and materials. These tools analyse and simulate the antenna's performance using numerical techniques and mathematical models. They allow engineers to adjust parameters such as antenna shape, size, materials, and environmental factors and analyse the antenna's performance across these varying conditions without the need for physical testing. Engineers can create accurate mathematical models by using EM simulation to obtain numerical results under various scenarios.

To sum up, the design and optimisation of antennas for a variety of applications depend heavily on antenna modelling. Engineers may evaluate antenna performance virtually with EM simulation tools, which eliminates the need for actual prototypes and testing and allows them to adjust design parameters and spot possible problems.

2 Problem and Motivation

Engineers commonly use electromagnetic (EM) simulation tools like Computer Simulation Technology (CST) Microwave Studio, High-Frequency Simulation Software (HFSS), and FEKO for antenna modelling. These tools enable designers to obtain performance metrics, including reflection coefficient, gain, radiation pattern, and impedance, without the need for costly and time-consuming prototype fabrication and testing. Electromagnetic simulations are based on solving Maxwell's equations, which describe the behaviour of electromagnetic waves and interactions between antennas and their environments. EM simulators offer significant advantages by delivering critical insights into antenna performance, including visual and numerical data on radiation patterns, gain, impedance, and bandwidth. According to these findings, designers can proficiently enhance antenna performance for certain applications. Moreover, electromagnetic simulations may evaluate antenna performance under diverse environmental circumstances and operational scenarios, examining the influence of variables such as temperature, humidity, conductivity, and proximate objects. These assessments are essential for guaranteeing the antenna's durability and dependability in practical settings. Nonetheless, electromagnetic simulation necessitates considerable computational resources, time, storage capacity, and expertise in electromagnetics. Traditional EM field analysis methods, such as the method of moments (MoM) and the finite element method (FEM), are computationally intensive due to the large number of formula calculations involved. With the progression of wireless communication technology, antenna design has garnered considerable focus, especially in radar systems, MIMO technology, and various wireless gadgets. Antenna design is pivotal for the transmission and reception of electromagnetic signals, profoundly influencing signal strength and quality. The growing intricacy of antenna configurations and design parameters may result in substantial processing requirements. Moreover, modern antenna simulations evaluate the radiator itself and consider factors like environmental conditions, connectors, installation fixtures, and system-level performance, making the simulation process more time-consuming.

Over the past years, machine learning (ML) has become more and more popular in antenna modelling and design because it can learn from measured and simulated antenna data to speed up the design and optimisation process. Antenna performance can be predicted in seconds by a well-trained machine learning model, which allows designers to assess performance across various design parameters considerably more quickly.

3 Antenna Design: From Traditional Methods to Artificial Intelligence

With the rapid development of modern communications systems and the increasing need for compact, lightweight, and high-performance antennas, microstrip antennas have emerged as a primary choice in many applications such as mobile phones, satellites, and wireless systems. However, the traditional design of these antennas often relies on theoretical calculations followed by iterative simulations using specialized software, followed by dimensional adjustments and re-simulations until the desired specifications are achieved. This process is time-consuming, requires significant computing resources, and may not always guarantee an optimal design.

On the other hand, artificial intelligence, specifically machine learning algorithms, has proven its great ability to address complex problems that link inputs and outputs in multivariable systems. By training models on data extracted from simulations or experiments, these algorithms can learn the nonlinear relationship between antenna parameters (such as patch dimensions, substrate thickness, and dielectric constant) and performance parameters (such as reflection coefficient, beamwidth, gain, and directivity). This makes it possible to predict antenna behavior or even propose new designs without the need for numerous simulation cycles.

Integrating artificial intelligence into antenna design not only reduces time and cost, but also opens new avenues for developing smart antennas that are adaptable to the operating environment. Recent years have witnessed a number of successful studies using artificial neural networks, support vector machines, random forest algorithms, and other predictive models to improve antenna performance and predict their parameters with high accuracy.

Therefore, combining electromagnetics and artificial intelligence represents a promising direction in scientific research, enabling the power of predictive modeling to be harnessed in the design and development of antennas for the next generation of smart communications systems.

4 State of the Art

Recent research efforts in antenna engineering have sought to overcome the limitations of classical design methods, which often depend on iterative and computationally expensive electromagnetic simulations. Two major directions have emerged: the use of advanced materials and structures—such as metamaterials, defected ground structures, and electromagnetic band-gap configurations—to enhance antenna performance, and the adoption of data-driven models that employ machine learning (ML) techniques. While material-based approaches improve bandwidth and efficiency, ML-based strategies provide accurate predictions of antenna parameters, reduce design time, and enable inverse modeling, where desired specifications are mapped directly to geometric dimensions. These developments signal a paradigm shift from trial-and-error methodologies toward faster, more adaptive design frameworks.

In the last decade, machine learning (ML) has attracted significant interest in antenna design due to its ability to accelerate optimization and reduce reliance on costly electromagnetic simulations. Early studies focused on artificial neural networks (ANNs) as surrogate models trained on data obtained from either simulations or measurements. These models demonstrated high predictive accuracy for key antenna parameters such as resonant frequency, bandwidth, and radiation efficiency, thereby minimizing the need for repeated full-wave simulations. Later contributions explored alternative algorithms, including support vector regression (SVR), decision trees, and ensemble methods like random forests, highlighting that the choice of algorithm can strongly influence accuracy and generalization.

Beyond performance prediction, ML has also been employed for inverse design, where target specifications (e.g., bandwidth or gain) are used as inputs to predict corresponding structural parameters. This approach represents a shift from traditional trial-and-error optimization toward automated and adaptive design strategies. However, inverse modeling remains challenging due to the highly nonlinear and sometimes non-unique mapping between antenna geometry and its electromagnetic performance.

A variety of surrogate modeling techniques have been developed to reduce computational cost. For example, [4] and [5] proposed efficient surrogate and inverse surrogate models for different antenna types, significantly lowering simulation time. Pietrenko-Dabrowska et al. citepietrenko2022reduced introduced methods capable of delivering reliable predictions even with limited training datasets. Similarly, Piltan et al. [6] applied deep learning to horn antenna design and achieved more than 80% computational savings compared to full-wave simulations, while maintaining accurate predictions of antenna gain.

Other contributions compared ML algorithms directly with classical techniques. For instance, Güneş [7] reported that support vector machines (SVMs) offered faster convergence and higher computational efficiency than ANNs in rectangular patch antenna design. Bayesian regularization methods were also applied to planar inverted-F antennas, improving prediction accuracy while reducing simulation requirements [8]. Linear regression, heuristic-enhanced ANNs, and multi-fidelity neural networks have been investigated for feasibility studies, embedded antenna modeling, and accurate performance optimization, respectively [9]. In reflectarray antenna design, Kriging models achieved substantial reductions in computational time while maintaining high accuracy.

Parallel to ML-based approaches, evolutionary algorithms such as genetic algorithms (GA) [10], swarm intelligence [11], and differential evolution (DE) [12] have been employed to optimize antenna structures. For instance, Silva and Martins [13] applied GA to ultra-wideband monopole antennas, while Oliveri et al. [14] used GA for 5G base station antennas. Swarm optimization was successfully applied by Dai and Luk [15] to suppress sidelobes in wideband millimeter-wave arrays, whereas particle swarm optimization (PSO), often combined with ANNs, was used in the design of multi-band patch and fractal antennas [15].

Overall, the literature emphasizes that ML-driven and evolutionary algorithms outperform traditional design methods in both accuracy and computational efficiency. Hybrid strategies—combining ML with evolutionary methods such as self-adaptive DE [12] or wind-driven optimization [16]—have shown remarkable potential for producing optimized antenna designs with faster convergence, reduced cost, and superior performance. Despite this progress, most studies still focus on single antenna types or specific algorithms, and many rely on relatively small datasets, limiting their generalization capability. These gaps motivate further research into systematic comparisons across models and the development of robust frameworks for practical antenna applications.

5 Author Contributions

In this thesis, our primary contribution lies in bridging the gap between traditional microstrip patch antenna design and modern predictive techniques through machine learning. We developed and evaluated multiple ML models—ANN, SVR, Decision Tree, and Random Forest—for accurately predicting antenna dimensions based on key performance indicators. By compiling and preprocessing a comprehensive dataset, we enabled efficient training and evaluation of these models. Our results showed that Random Forest and ANN significantly reduced prediction errors compared to conventional design approaches. We introduced a systematic methodology for integrating ML into antenna engineering workflows, enhancing both speed and accuracy. Additionally, we conducted a detailed comparative analysis of model performance using MSE and MAE as benchmarks. Our work demonstrates a viable path toward intelligent, data-driven antenna design. This research lays the groundwork for further exploration of AI in electromagnetics and wireless engineering.

6 Thesis Organization

After having been seen in Chapter 1, which provided an introduction to the background of the study, a clear explanation of the research problem, and the motivation behind the work, the structure of the dissertation was outlined to guide the reader through the remainder of the research process. The chapter concluded with a section on thesis organisation, offering a structured overview of the subsequent chapters and illustrating the logical progression of the investigation.

Chapter 2 will investigate microstrip patch antennas: state-of-the-art, presenting an in-depth review of the history, design principles, feeding techniques, and analysis methods for microstrip antennas. It also covers key antenna parameters and their applications in various fields.

Chapter 3 will present machine learning, explaining its definition, history, and different learning approaches, including supervised, unsupervised, semi-supervised, and reinforcement learning. The chapter also explores deep learning techniques and neural network architectures, which serve as foundational tools for predicting antenna dimensions.

Finally, Chapter 4 focuses on comparing different machine learning models used to predict the dimensions of rectangular patch antennas. The chapter starts by describing the antenna structure and how the dataset was collected. It includes information on the antenna's geometric parameters and the key performance metrics used, such as return loss, bandwidth, and resonant frequency.

Next, the chapter presents the implementation of four machine learning algorithms: Artificial Neural Networks (ANN), Support Vector Regression

(SVR), Random Forest, and Decision Tree. These models are evaluated based on their accuracy using performance metrics like Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).The results from each model are then compared, showing how well they predict the antenna dimensions. Random Forest showed the best performance, achieving the lowest error among the models tested.

Finally, the chapter discusses the concept of inverse modeling, where the desired antenna performance is used to predict its dimensions. This approach helps to save time and improve design accuracy without relying on repeated simulations.

CHAPTER 2

Microstrip Patch Antennas

1 Introduction

Antennas are crucial and essential components of wireless communication systems. Between the transmitter and receiver, it serves as a coupling device. It is an apparatus that emits and receives radio waves. Antennas with multiband functioning are becoming more and more in demand these days. As a result, it has drawn numerous researchers to conduct studies on cutting-edge antenna varieties. Microstrip patch antennas have several special qualities and advantages over conventional antennas. Microstrip patch antennas are quite effective and adaptable in terms of their geometric patterns and real-world applications. There are different types of antennas, like loop antennas, reflector antennas, aperture antennas, lens antennas, microstrip patch antennas, etc.[17]. One of the most adaptable and conformal antennas among them is the microstrip patch antenna. Designing and fabricating it is simple.

2 History of patch antenna

About 66 years prior, in 1953, G. A. Deschamps [18] proposed that the first microstrip antenna was perceived in the United States. After a short two-year period, H. Gutton and G. Baissinot patented microstrip antennas in 1955 for their creation of a flat aerial appropriate for the UHF band [19]. E. V. Byron [20] created the first workable microstrip radiator in the early 1970s after a lengthy period of roughly 15 years. A dielectric strip spanning multiple long-half wavelengths separates the conducting strip of this radiator from a ground plane. Through the coaxial connector, the radiator receives periodic excitation from the antenna's bottom side. R. E. Munson [21] created an antenna in 1974 using a phased array and suggested methods to get around limited bandwidth restrictions by adding a height dielectric and loading slots and notches in radiator strips. Antennas with phased arrays have a radiating aperture on their upper side. A year later, in 1975, J. Q. Howell [22] proposed an antenna with CP and linearity made up of simple patches with circular and rectangular shapes. The antenna has a ground and a parallel thin radiating element that are separated by a dielectric substrate ($t < \lambda$). The bandwidth of the antenna is typically a fraction of a percent to a few percent, depending on the thickness and dielectric constant. In 1979, researchers A. Van de Capelle et al. [23] put forth two strategies for expanding an antenna's bandwidth in order to get around its restrictions. While the second method entails developing a broadband-frequency autonomous microstrip antenna, the first method entails establishing two or more thin antenna bands with distinct operating frequencies. In 1980, author C. Wood [24] proposed a novel approach to antenna design by positioning two $\frac{\lambda_m}{4}$ short-circuit parasitic components at radiating edges with a capacitive nature. Nevertheless, the physical volume of the antenna design is increased by about two times when parasitic elements are added to an excited patch BW. The technique can be applied to more complex designs, such as linearly polarised antennas and circularly polarised elements. After 1980, many researchers proposed various antenna design strategies and ideas, and the antenna's performance improved.

3 Overview of Microstrip Antenna

Microstrip patch antennas (MPAs) are inexpensive, lightweight, low-profile, easy to fabricate, and simple. It is one of the most extensively studied and used components for numerous applications in space communication, radar engineering, military systems, mobile radio, wireless communication, etc. because of these exceptional qualities. As seen in Figure 1, it has a radiating metallization area known as a "patch" that is positioned above the grounded substrate and is supplied with energy via a suitable feeding mechanism [**James1989handbook**, 17, 25]. The TM modes are excited by the traditional patch, which is a perfect electric conductor (PEC). Surface magnetic currents are produced by the radiating edges of the cavity between the patch and substrate. This is in line with the radiation at the patch [26].

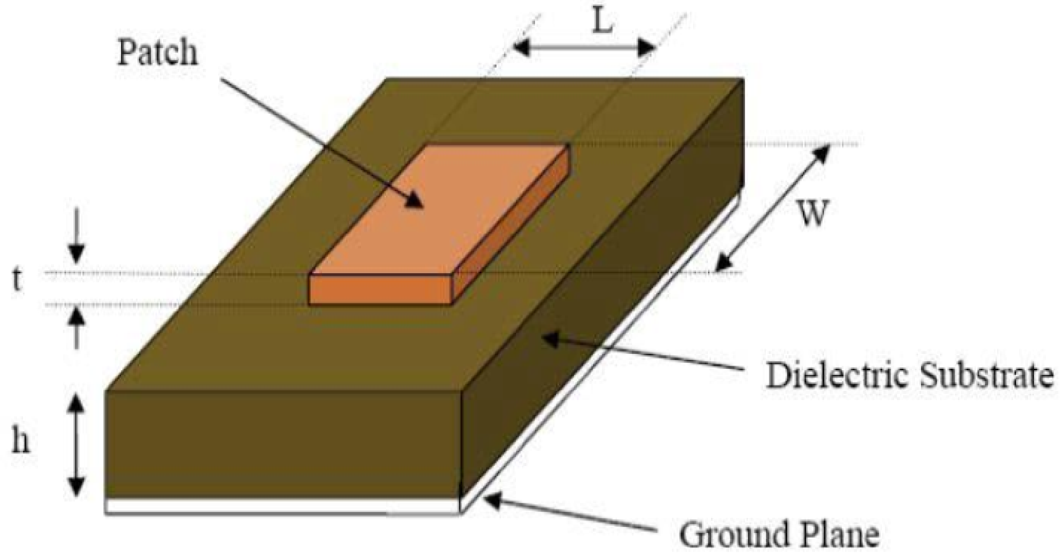

Figure 1: Rectangular microstrip patch antenna. [27]

The radiating conductor patch may take any shape: circular, rectangular, triangular, or any arbitrary formation, as shown in Figure 2. Depending on the patch shape, MPAs are flexible in terms of impedance parameters – resonant frequency, bandwidth, and radiation characteristics such as pattern, polarization, gain, etc [28, 29]. Therefore, to ensure optimal performance, we must optimise the antenna's shape and dimension based on the system requirements.

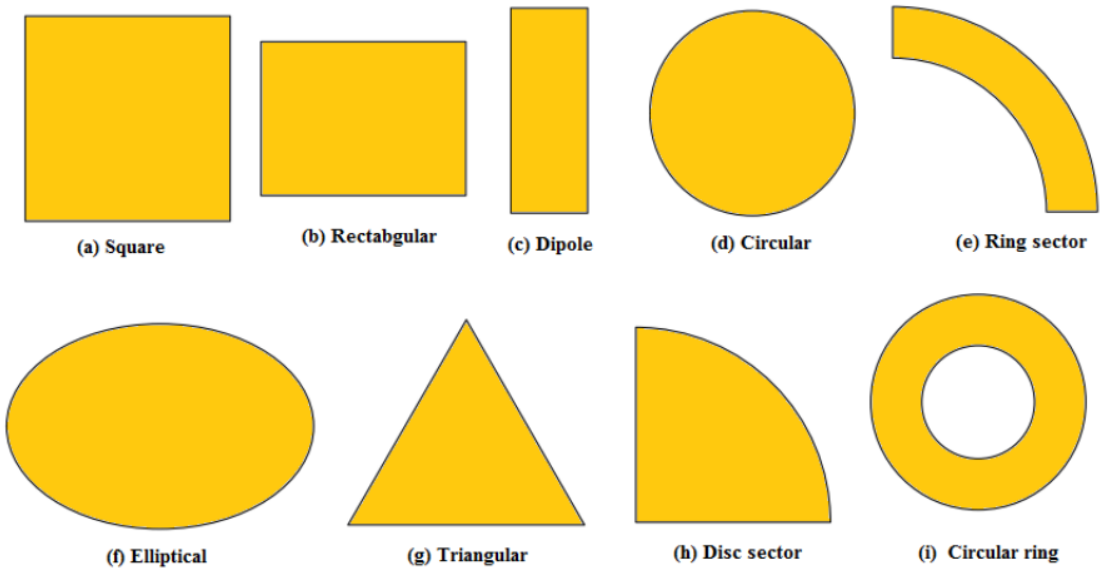

Figure 2: Various antenna patch shapes. [30]

These microstrip antennas also have a few major disadvantages, such as low efficiency, less power, small gain, spurious feed radiations, surface waves, narrow bandwidth, etc. This limits the applications where it may be used [25, 31]. Various methods aim to improve these impedance and radiation parameters as desired.

4 Feeding techniques

The feeding techniques of microstrip patch antennas are classified into four types. They are microstrip feed line, coaxial feed line, aperture coupled feed, and proximity coupled feed [25].

4.1 Microstrip Feed Line:

In the microstrip feed line technique, a conducting strip is directly connected to the radiating patch as shown in Figure 3. Compared to the radiating patch, the conducting strip's width is narrower. The significance of this configuration lies in the fact that the feed can be etched onto the same substrate, resulting in a planar structure. To obtain good impedance matching, an inset cut can be incorporated into the patch. This prevents the use of additional matching elements. These techniques provide easy fabrication and simplicity in modelling.

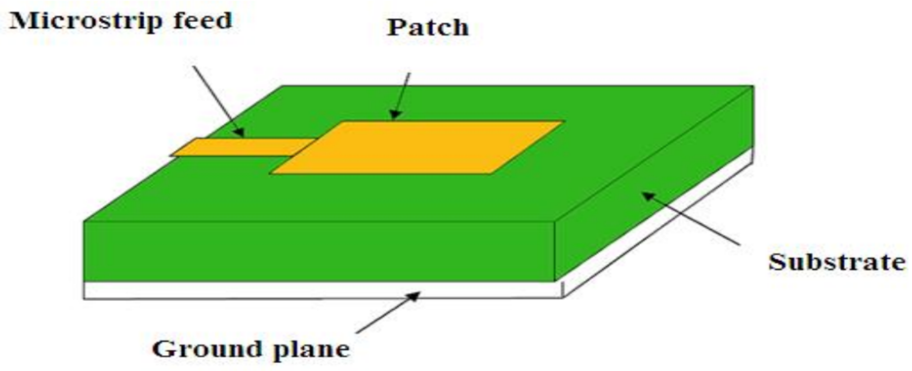

Figure 3: Microstrip feed line [32].

4.2 Coaxial Feed Line:

We refer to the coaxial feed technique as the probe feed method. The coaxial feed consists of two conductors, namely the inner conductor and the outer conductor. The inner conductor of the coaxial cable passes through the dielectric substrate and is connected to the radiating patch as shown in Figure 4. The outer conductor connects to the ground plane. The significance of this feeding lies in its ability to align impedance at any desired position within the patch. It is simple to fabricate and has low spurious radiation effects. Its major disadvantage is that it provides a narrow bandwidth. This feed technique has certain disadvantages.

- It provides a narrow bandwidth.
- Fabrication is challenging because a hole needs to be drilled into the substrate.
- Thicker substrate leads to matching problems.

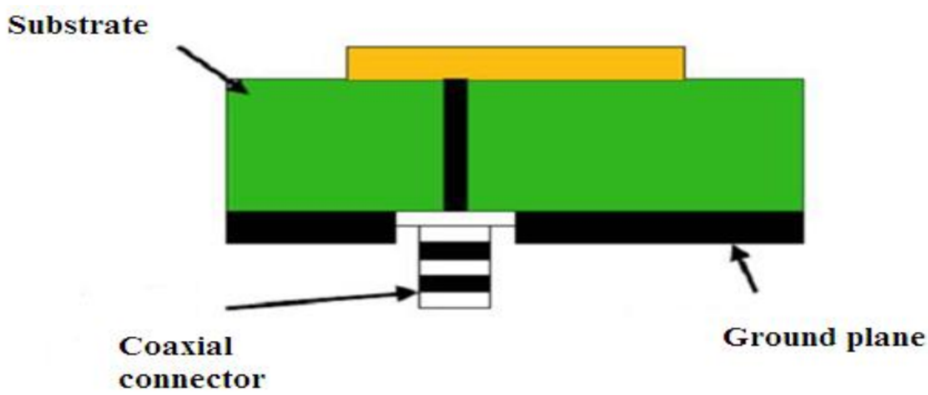

Figure 4: Coaxial feed [33].

4.3 Aperture Coupled Feed:

In the aperture coupling feed, on the top of the antenna substrate, the radiating patch is etched, and on the bottom of the substrate, a microstrip feed line is etched, as shown in Figure 5. This provides proper aperture coupling. To enhance the unique electrical properties of radiation and circuitry, the thickness and dielectric constants can be selected independently. A coupling aperture is typically positioned at the centre beneath the patch. This leads to lower cross-polarisation. The configuration, dimensions, and position of the aperture dictate the degree of coupling from the feed line to the patch. To optimise radiation from the patch, the top substrate is made of a thick dielectric constant material, and the bottom substrate is made of high dielectric material. The main advantage of this feed is that the effect of spurious radiation is minimised.

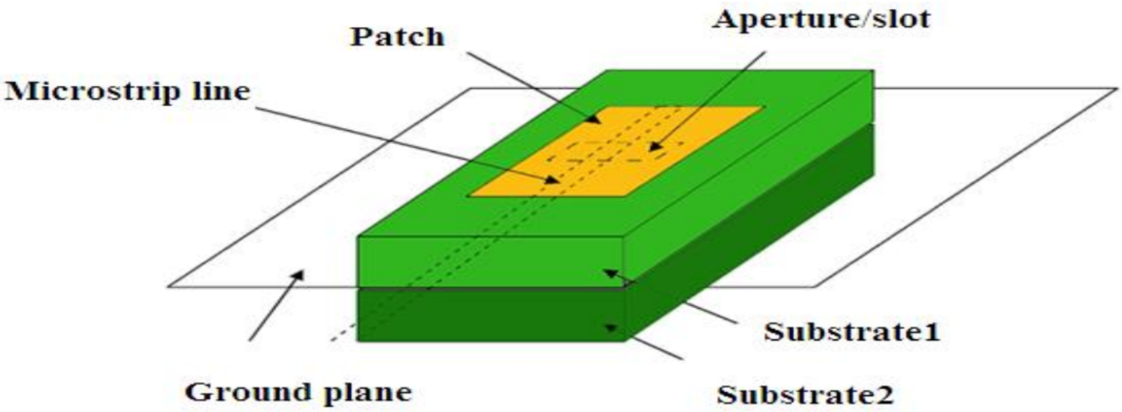

Figure 5: Aperture coupled feed [34].

4.4 Proximity Coupled Feed:

The proximity-coupled feed method There are two dielectric substrates used. As illustrated in Figure 6, the radiating patch is printed on top of the upper substrate, and the feed line is positioned in between the substrates. This feeding method has the advantage of having a very high bandwidth and minimising spurious feed radiation.

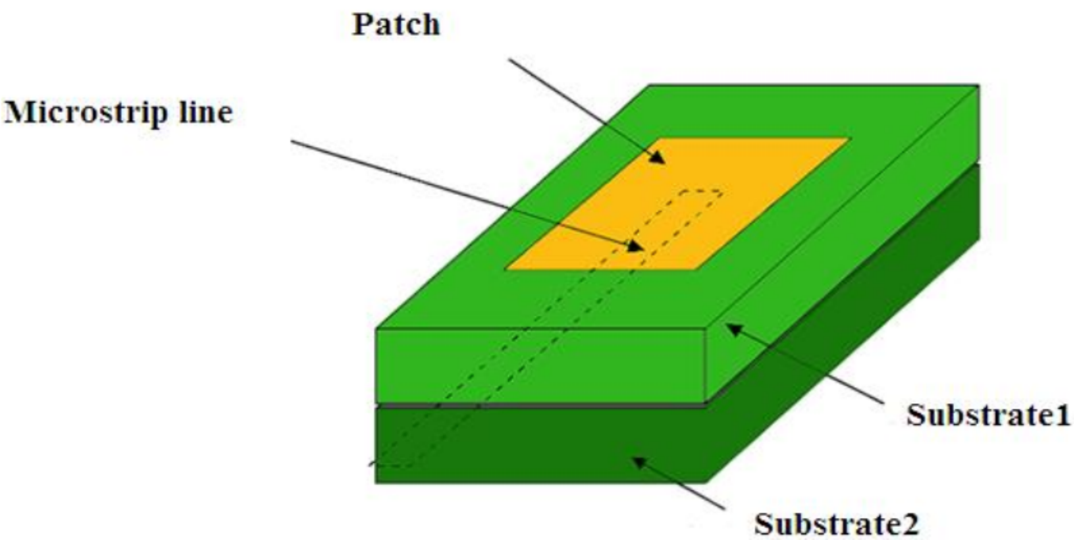

Figure 6: Proximity coupled feed [35].

4.5 Comparison of different feeding techniques

A comparison is made between the four different feeding techniques described in the foregoing sections. Table 1 provides the list of the parameters selected for the purpose of comparison. They are, namely, spurious radiation due to feed, reliability, ease of fabrication of the feed, and the bandwidth obtained. It appears that the aperture-coupled feeding technique offers less spurious radiation. Reliability is good in both aperture-coupled and proximity-coupled methods. As can be delineated from the previous discussions, fabricating a microstrip line feed is much easier compared to the other three techniques. The proximity-coupled feeding method offers an enormous advantage in terms of bandwidth enhancement. It is therefore suggested to select the method of feeding the microstrip antennas depending on the specific requirement of the application in question.

Characteristics	Microstrip line feed	Coaxial feed	Aperture coupled feed	Proximity coupled feed
Spurious feed radiation	More	More	Less	Medium
Reliability	Better	Poor	Good	Good
Ease of fabrication	Easy	Soldering and drilling required	Alignment required	Alignment required
Bandwidth achieved	2-5%	2-5%	2-5%	13%

Table 1: Comparison of performance characteristics between different feeding techniques [36].

5 Methods of Analysis

Many techniques exist for microstrip antenna analysis; however, just three—transmission line, full wave, and cavity model—are particularly prominent and widely regarded. Among these models, the accuracy of the transmission line is minimal; however, it is the simplest and more challenging to model. The cavity model exhibits greater accuracy compared to the transmission model, albeit with increased complexity. IIn addition to these two analytical models, the whole wave model demonstrates good accuracy and greater versatility, although it comes with increased modelling complexity.

5.1 Transmission Line Method

The transmission model is the simplest of all; however, it exhibits lower accuracy and versatility. This technique represents the microstrip antenna as two thin apertures, each with a height (h) and width (w), separated by a length L. In a microstrip antenna, the substrate and air exhibit non-uniform electric field lines due to the presence of two dielectrics. A significant quantity of electric field lines traverses the substrate, with a limited number partially residing in the air. The patch emits radiation through corners and is encircled by fringing fields that are not solely concentrated within the dielectric, although some extend into the air. The effective dielectric (ε_{eff}) is marginally lower than (ε_r). The effective dielectric (ε_{eff}) can be articulated as [25].

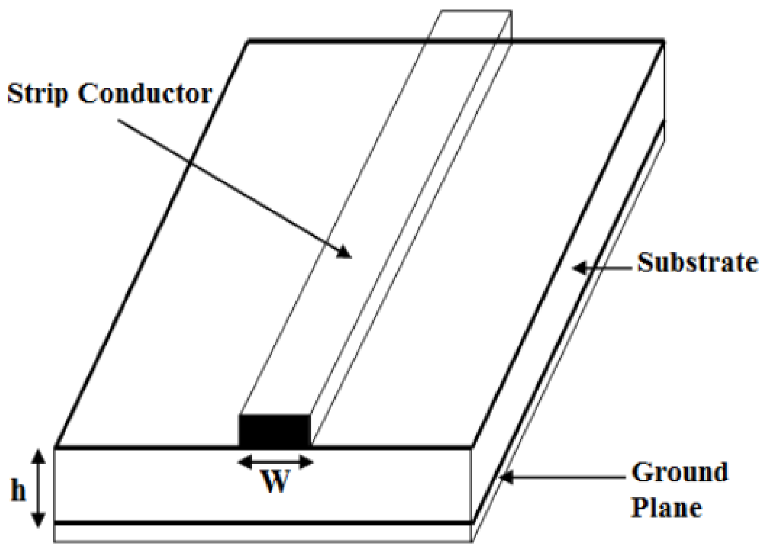

Figure 7: Microstrip line.

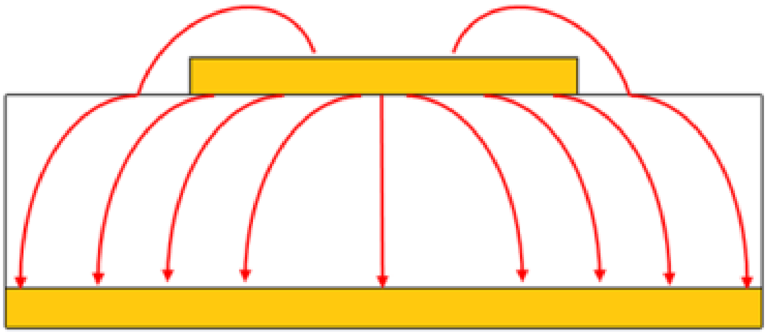

Figure 8: Electric field lines (Side view) [25].

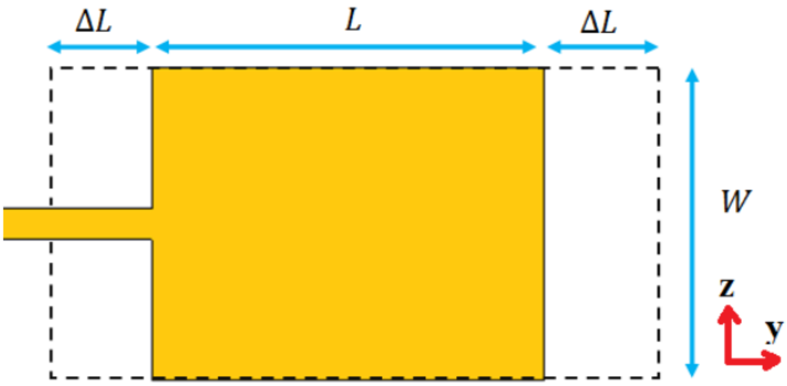

Figure 9: Electric field lines (Top view) [25].

$$\varepsilon_{\text{eff}} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left(1 + 12\frac{h}{w}\right)^{-\frac{1}{2}} \tag{1}$$

Where,

ε_{eff} = Effective relative permittivity

ε_r = Relative permittivity

h = Substrate thickness

w = Patch width

5.2 Cavity Model

This model characterises the region between the ground antenna and the radiating patch as a cavity, bounded by magnetic walls on the periphery and electric walls on the top and lower sides. The field might be regarded as homogeneous within the cavity owing to the slender substrate in the direction of its thickness. The fringing fields throughout the perimeter are evaluated by considering the exterior of the patch boundary, resulting in physical patch parameters that are somewhat lower than the effective dimensions. The conductor loss and the radiation effect from the antenna are taken into account by incorporating these losses into the dielectric material as a loss tangent. The emitted power and distant field at the edges of the radiating patch are analysed based on the equivalent magnetic current. In the cavity model, an alternative technique can be employed by applying an impedance boundary condition to the cavity walls, thereby incorporating the radiation effect. Both radiated power and fringing fields have been concentrated at the cavity's side. The cavity excludes them.

5.3 Method of Moments (MOM)

In MOM, polarization currents and surface currents are employed to represent the fields within dielectric slabs and microstrip patches, respectively. An integral equation is constructed to assess feed lines and their impact on the ground, as well as the unknown currents on the patches, which is subsequently transformed into algebraic equations. Thus, they can be readily resolved. This investigative approach takes into account the fringing field outside the physical boundary of the patch, thereby providing a precise solution.

6 Antenna Parameters

Antenna parameters describe the antenna's performance. These may be interrelated to each other. The antenna parameters are measured in far-field range, near-field range, or free-space range [37]

6.1 Bandwidth

An antenna's bandwidth (BW) is the frequency range in which it can transmit and receive signals efficiently; it is also the frequency range in which it can receive radiations. For an antenna to function well and cover a large frequency range, impedance matching must be maintained. The antenna's reflection coefficient plot is taken into consideration in order to calculate its BW. As seen in Figure 10, bandwidth is defined as the difference of two frequencies observed at the points where the reflection coefficient plot intercepts the -10dB line. Lower cut-off (f_l) and higher cut-off (f_h) are the terms used to describe the values of the two frequencies mentioned above. The bandwidth calculation formula is shown below in equation 2.

$$Bandwidth(inHz) = (f_h) - (f_l) \tag{2}$$

The percentage bandwidth is also calculated by the formula given below in equation 3.

$$\text{Bandwidth} = \frac{f_h - f_l}{\frac{f_h + f_l}{2}} \times 100\% \tag{3}$$

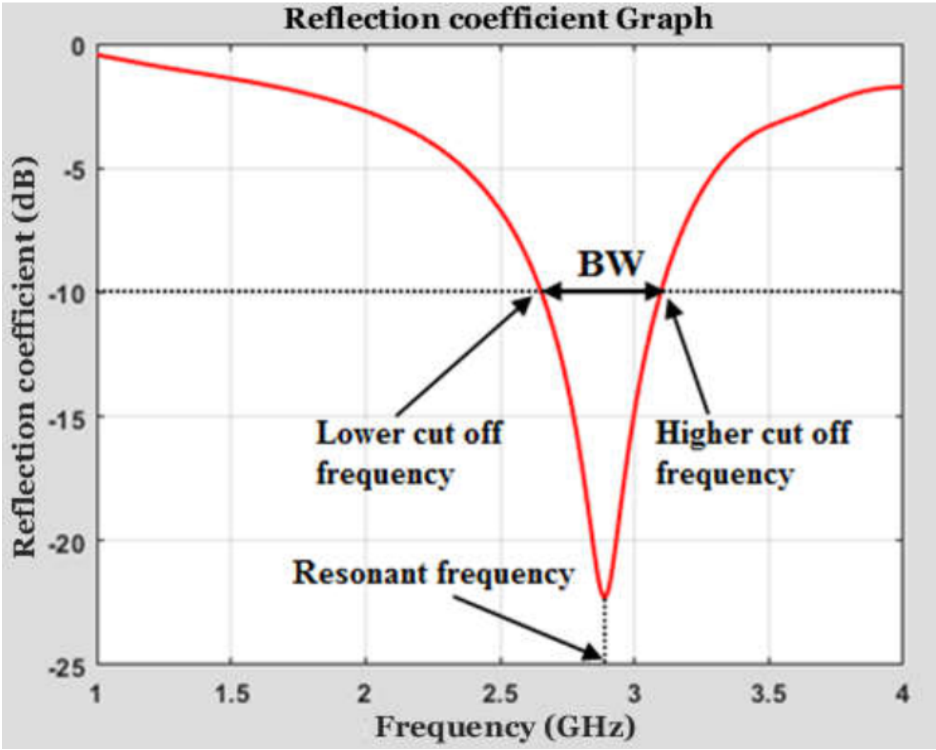

Figure 10: Antenna bandwidth with reflection coefficient graph.

6.2 VSWR (Voltage Standing Wave Ratio)

The maximum voltage (Vmax) to minimum voltage (Vmin) ratio gives antenna VSWR. Equation 4 has been utilized for calculating VSWR as given below.

$$\text{VSWR} = \frac{V_{\text{max}}}{V_{\text{min}}} \tag{4}$$

$$\text{VSWR} = \frac{1+\Gamma}{1-\Gamma} \tag{5}$$

where,

$$Z_l = \text{Load Impedance} \quad Z_0 = \text{Characteristic Impedance} \tag{6}$$

VSWR indicates how closely the input and characteristic impedance match. A larger mismatch is indicated by a high VSWR value. The antenna must have a VSWR greater than 1.5:1 against an impedance of 50 Ω in order to function properly. Assuming that no power is reflected and that all energy is received by the input terminal, VSWR for a perfectly matched system is 1:1.

6.3 Antenna Gain

We have used an isotropic antenna as a reference to evaluate gain, ensuring equal input power to the test antenna. We hypothetically assume that the antenna emits uniform radiation in all directions. The directivity of such antennas is expressed as 0 dB, indicating uniform emission in all directions. In a certain direction, gain is the ratio of maximum intensity to isotropic intensity, both supplied by the same input power to the antennas. The isotropic intensity, representing the power emitted uniformly in all directions, is equivalent to the power input received by the antenna divided by 4π. The unit of gain is decibels (dB). It is mathematically represented as follows [25].

$$\text{Gain} = \frac{4\pi\,(\text{Radiation Intensity})}{\text{Total Input Power}} = \frac{4\pi\,U(\theta,\phi)}{P_{\text{in}}} \tag{7}$$

Gain in terms of directivity is given as

$$\text{Gain} = \eta \cdot D \tag{8}$$

Where,

η is efficiency and D is directivity.

6.4 Directivity

Antenna directivity is defined as the ratio of radiation intensity in a particular direction to the average radiation intensity across all directions. The average radiation intensity is regarded as a fraction of the total radiated power divided by 4π. It is represented by the symbol D and mathematically articulated as follows [25].

$$D = \frac{U}{U_0} = \frac{4\pi U}{P_{\text{rad}}} \tag{9}$$

Where,

U = Intensity of radiation in specific a direction.

U_0 = Average intensity of radiation intensity in overall direction.

P_{rad} = Total radiated power.

6.5 Antenna Efficiency

It is defined as the ratio of radiated power to the total input power supplied to the antenna. It is represented by the symbol η and mathematically articulated as follows [25].

$$\eta = \frac{\text{Power radiated}\,(P_{\text{rad}})}{\text{Total input power}\,(P_{\text{in}})} \tag{10}$$

$$\eta = \frac{P_{\text{rad}}}{P_{\text{rad}} + P_{\text{l}}} \tag{11}$$

Where,

P_{rad} = Power radiated.

P_{l} = Ohmic losses.

Mathematically, it also expressed in terms of Quality factor (Q) as

$$\eta = \frac{Q_t}{Q_{\text{rad}}} \tag{12}$$

Where,

Q_{t} = Q factor of total power.

Q_{rad} = Q factor of radiated power.

In general, total efficiency η_0 also expressed mathematically as

$$\eta_0 = (\eta)_r \cdot (\eta)_c \cdot (\eta)_d \tag{13}$$

Were,

$(\eta)_r$ = Efficiency of reflection.

$(\eta)_c$ = Efficiency of conduction.

$(\eta)_d$ = Dielectric efficiency

6.6 Input Impedance

To achieve optimal energy transfer between the antenna and transmission line, the input impedance (Z_{in}) must be precisely matched to the characteristic impedance (Z_0). If the matching between both is imperfect, a reflected wave will be formed at the antenna end, going toward the source. This resulted in a decrease in efficiency when the antenna is employed for energy transmission or reception. The ratio of electric field components to magnetic field components at a specific site is referred to as input impedance. The voltage-to-current ratio at any point without a load can be represented as the antenna's impedance, as indicated below [25].

$$Z_A = R_A + jX_A \tag{14}$$

Were,

Z_A = Antenna impedance.

R_A = Antenna resistance.

X_A = Antenna reactance

6.7 Beamwidth

Beamwidth is the angular distance between two symmetrically placed points on either side of the main lobe pattern. There are several symmetrical locations on both sides of a primary pattern, but only one point, at the half-power value, is assigned to beamwidth (the half-power point). Half-power beamwidth, frequently shortened to HPBW, is the angular separation between symmetrically positioned half-power points in the plane of maximum beam direction. Apart from the half-power beamwidth (HPBW), another important indicator of the beamwidth of the radiation pattern is the first null beamwidth (FNBW).

6.8 Radiation Intensity

Radiation intensity is the amount of power that an antenna radiates per unit solid angle. The far-field parameter can be found by simply multiplying the radiation density by the square of the distance. It can be stated mathematically as follows [25].

$$U = r^2 \cdot W_{\text{rad}} \tag{15}$$

Were,

W_{rad} = Radiation density.

r = Distance.

U = Radiation intensity

6.9 Beam Efficiency

The quality of both transmitting and receiving antennas is typically employed to assess beam efficiency (BE). Beam efficiency is defined as follows [25] for any antenna that is orientated with its main lobe directed along the positive z-axis ($\theta = 0°$).

$$BE = \frac{\text{Power transmitted (received) in the cone angle } \theta_1}{\text{Power transmitted by the antenna.}} \tag{16}$$

Where,

θ_1 = Half-angle of cone in which % of total power is associated.

6.10 Polarization

The polarization of a single-frequency electromagnetic wave is a distinctive trait, as it delineates both the orientation and shape over time. Polarisation refers to how the electric field vector of an electromagnetic wave changes direction and strength over time. Polarization is classified into three distinct categories, as illustrated below.

1. Linear polarization
2. Circular polarization
3. Elliptical polarization

In electromagnetic wave propagation, polarization is crucial for the interaction between transmitting and receiving antennas. Power transfer is maximised when both the receiving antenna and the incident wave exhibit identical direction and polarisation; otherwise, power loss ensues due to polarisation mismatches.

6.11 Radiation Pattern

The radiation pattern of an antenna is defined as "a graphical representation or a mathematical relationship of the radiation characteristics as a function of spatial coordinates". The far-field region frequently employs this pattern. Consequently, the radiation pattern illustrates the spatial distribution of the electromagnetic field emitted by the antenna. Two planes, the H-plane and E-plane, illustrate the pattern. The h-plane contains the magnetic field vector and the direction of maximum radiation, while the E-plane encompasses the electric field vector and its corresponding maximum radiation direction. Pattern attributes encompass radiation intensity, power flux density, directivity, field strength, polarization, and phase. It also encompasses infinite E-planes for each ϕ in the elevation plane and a singular H-plane for $\theta = 90°$ in the azimuth plane.

7 Advantages, Limitations, and Applications of Microstrip Antennas

Microstrip antennas have many benefits over traditional microwave antennas [38]:

- Lightweight, low volume, and thin profile configuration, which can be made conformal.
- Low fabrication cast; easily suitable for mass production.
- Linear and circular polarization.
- Antennas capable of dual-frequency and dual-polarization can be readily fabricated.
- Backing cavity is not required.
- Integrability with microwave integrated circuit.

Nonetheless, microstrip antennas possess certain limitations in comparison to traditional microwave antennas [38]:

- Narrow bandwidth.
- Lower gain.
- Difficult Polarization purity.
- Lower power handling capability.
- Reduced gain and efficiency.
- Surface waves Excitation.

8 Applications of Microstrip Antennas

Because of their small size and flat shape, microstrip antennas are widely used in many commercial and military applications, such as telemetry and missile systems. Satellites and several high-performance applications have utilised the small size of microstrip antennas. Their main uses are in security applications, radar systems, and mobile devices. Altimeters in satellite imaging and radar systems have used small microstrip radiator arrays. Its slim form fits perfectly with sophisticated weapons. Pagers, GPS, and GSM systems all make considerable use of microstrip antennas.

8.1 Global Positioning System Applications

At first, the government only used satellite-based GPS for military applications, but today it is widely used in many different industries. Each satellite simultaneously transmits codes at two different frequencies while operating in the L-band. The ground terminal requires an all-encompassing, omnidirectional antenna. One of the best options for reducing size, weight, and expense in the L-band is a microstrip antenna. Microstrip antennas are incredibly tiny in mass and size. These features imply that finding a different kind of antenna for GPS applications that performs as well as microstrip antennas is quite challenging.

8.2 Mobile and Satellite Communication

Both satellite and mobile require low-profile, small devices with inexpensive antennas. In satellite communication, square and circular patches with several feed points are quite helpful. Numerous types of microstrip antennas have been used in mobile systems, and they have all the characteristics of other antennas.

8.3 Radio Frequency Identification

Depending on the application, RFID systems typically use frequencies between 125 kHz and 5.8 GHz with the aid of an antenna. The transponder and transceiver are the two main components of the RFID system. RFID is used in a wide range of industries, including manufacturing, transportation, logistics, mobile communication, and healthcare.

8.4 Worldwide Interoperability for Microwave Access

WiMAX is an IEEE 802.16 application standard that, in theory, can transmit data at a speed of 70 Mbps up to 30 miles. Patch antennas have been used in WiMAX-compliant communication devices and radiate at three resonance frequencies: 2.7 GHz, 3.3 GHz, and 5.3 GHz.

8.5 Radar Application

Low-profile, lightweight antennas are necessary for radar system applications. Microstrip patch antennas are the best option for it. Moving targets can be detected using radar. The production process, which depended on photolithography, produced a large number of patch antennas with reliable performance at a reasonable cost in a shorter amount of time than previous basic antennas.

8.6 Medical Hyperthermia

Because it matches perfectly at specified areas and doesn't leak energy beyond the treated area, microwave energy is a valuable type of heating that works well for treating malignant tumors in medical studies. For this reason, the antenna's radiator must be lightweight and controllable. Consequently, a microstrip patch radiator meets each of these specifications.

9 Summarize

Chapter 2 offers an in-depth primer on microstrip patch antennas, exploring their history, design principles, and various feeding techniques. It begins with a discussion of the antenna's evolution and its essential characteristics, followed by an in-depth look at the different feeding methods, including microstrip, coaxial, aperture-coupled, and proximity-coupled feeds, each with its advantages and limitations. The chapter also covers the primary methods of analysis, such as the transmission line method, the cavity model, and the method of moments (MOM), which are used to model antenna behaviour. Key antenna parameters, like bandwidth, VSWR, gain, directivity, efficiency, and radiation pattern, are examined, emphasising their role in optimising antenna performance. Additionally, the chapter highlights the diverse applications of microstrip antennas, including GPS, satellite communication, RFID, radar, and medical fields, showcasing their versatility. Overall, this chapter establishes the foundational knowledge necessary for understanding microstrip patch antennas and their wide range of practical applications in modern communication systems.

CHAPTER 3

Machine Learning

1 Introduction

Recent years have seen a significant increase in interest in artificial intelligence (AI), with professionals from a wide range of industries hoping to use it to make their work more efficient. AI is used, for instance, by economists to forecast market prices in order to maximise profits, by physicians to identify benign or malignant tumours, by meteorologists to forecast the weather, and by recruiters to examine resumes and assess whether candidates fit the requirements of the position. One of the most significant and potent technologies of our time is machine learning in particular. Although its full potential is still a long way off, AI will undoubtedly continue to be a hot topic of conversation for some time to come [39].

2 Machine Learning Definition

Machine Learning (ML) is a form of artificial intelligence and a technique for analysing data. It alludes to the automation of the process of developing analytical models, which is based on the idea that systems can learn from data, spot trends, and come to conclusions with little assistance from humans. In order to teach computers to recognise patterns in data for future forecasts and predictions or as a quality evaluation for performance improvement, a variety of algorithms are used. Computers can learn on their own without explicit programming thanks to machine learning. [40]. Smartphones and other smart devices have machine learning features, as demonstrated by features like speech recognition, predictive text, and computational photography. Smart devices can become more proactive and intuitive thanks to machine learning. Machine learning (ML), which depends on vast amounts of data, is frequently connected to smart devices via the Internet of Things (IoT).

3 History of Machine Learning

AI and machine learning algorithms are not a recent development. For years, scientists and researchers have explored whether computers can possess true intelligence by learning independently, without human intervention.

Machine learning was first conceptualised in the 1950s. One of the first machine learning programmes was created by IBM researcher Arthur Lee Samuels; it was a self-learning checker-playing programme. In addition, he is credited with creating the term "machine learning." A 1959 article in the IBM Journal of Research and Development described his methodology [41].Research and experimentation were the main sources of advancement in the field from the 1950s until the early 2000s. Frank Rosenblatt developed the perceptron, the first neural network for computers, in 1957. It replicated the functions of the human brain. Students at Stanford University created the "Stanford Cart" in 1979, which could move through obstacles on its own. The idea of explanation-based learning (EBL), first proposed by Gerald Dejong in the 1980s, involves computers analysing training data to produce generalised rules by eliminating irrelevant information.Machine learning changed from being knowledge-driven to being data-driven in the 1990s. Scientists started creating software that enabled computers to analyse enormous volumes of data and "learn" from the outcomes.Tech behemoths like Microsoft, IBM, and Facebook, as well as industrial firms like Tesla, are currently engaged in intense competition to create machine learning-based programmes and products that function without human supervision.

4 Types of Machine Learning Approaches

Many machine learning models are characterised by the level of human involvement with the raw data, whether by offering rewards, providing specific feedback, or applying labels [22].

- Supervised learning
- Unsupervised learning
- Semi-supervised learning
- Reinforcement learning

4.1 Supervised learning

Supervised learning is a machine learning approach that depends on datasets with labels. These datasets are used to train or "supervise" algorithms, helping them classify data or predict outcomes with precision. By using labelled inputs and outputs, the model can evaluate its performance and enhance its learning over time [42].

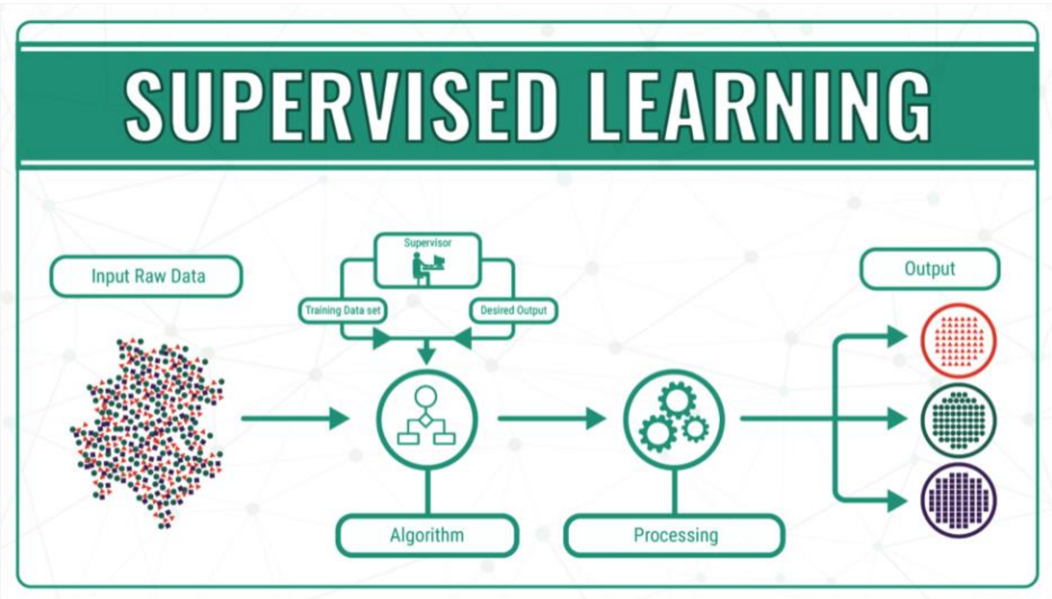

Figure 11: Supervised Learning.

In data mining, supervised learning can be categorized into two types of problems: classification and regression:

4.1.1 Classification

Classification problems involve using an algorithm to correctly categorise test data into specific groups, such as distinguishing apples from oranges. In practical applications, supervised learning algorithms can be employed to sort spam emails into a separate folder from your inbox. Prevalent categories of classification algorithms encompass linear classifiers, support vector machines, decision trees, and random forests.

4.1.2 Regression

Regression is a form of supervised learning that employs an algorithm to examine the relationship between dependent and independent variables. Regression models are effective for forecasting numerical values from diverse data points, such as projecting sales revenue for a business.

- **Linear regression:** Before diving into linear regression, let's first understand the concept of regression. Regression is a technique used to model a target value based on independent predictors. It is primarily used for prediction and identifying cause-and-effect relationships between variables. The various types of regression differ mainly in the number of independent variables and the nature of the relationship between the independent and dependent variables.

  Simple linear regression is a type of regression analysis where there is only one independent variable, and the relationship between the independent variable (x) and the dependent variable (y) is linear. The red line in the graph above represents the "line of best fit", which is drawn to best represent the given data points. This line is determined using the linear equation outlined below.

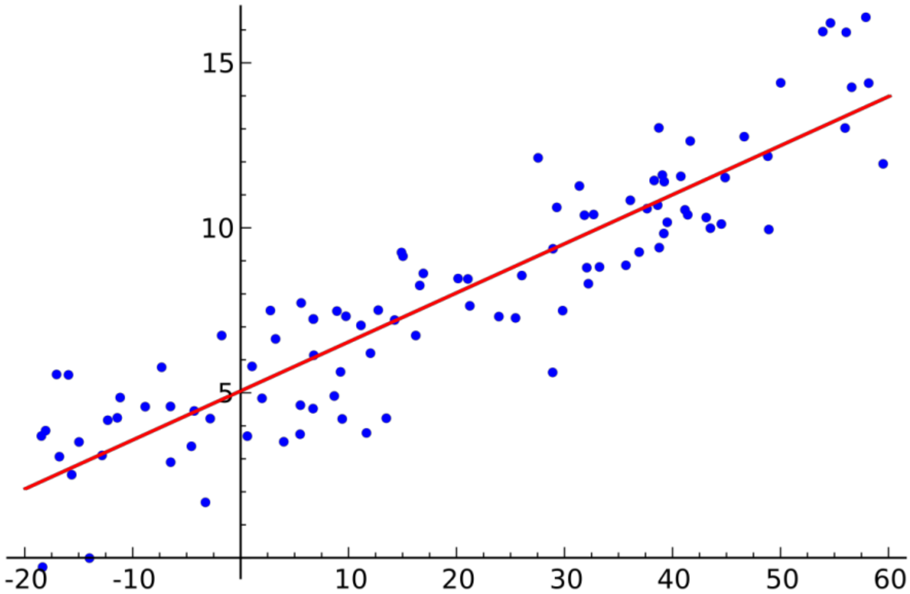

Figure 12: Linear regression.

- **Logistic regression:**

  Logistic regression is one of the most well-known machine learning algorithms, following closely behind linear regression. While linear and logistic regression share many similarities, their main distinction lies in their applications. Linear regression is used for predicting continuous values, whereas logistic regression is applied to classification tasks. If you're unfamiliar with linear regression, it may be helpful to explore its concepts further. Classification tasks are common in many everyday scenarios, such as determining whether an email is spam, identifying whether a tumour is malignant or benign, or classifying whether a website is fraudulent. These are all common examples where machine learning algorithms can significantly impact our lives. A simple yet effective classification algorithm is logistic regression. Let's now take a closer look at how logistic regression works.

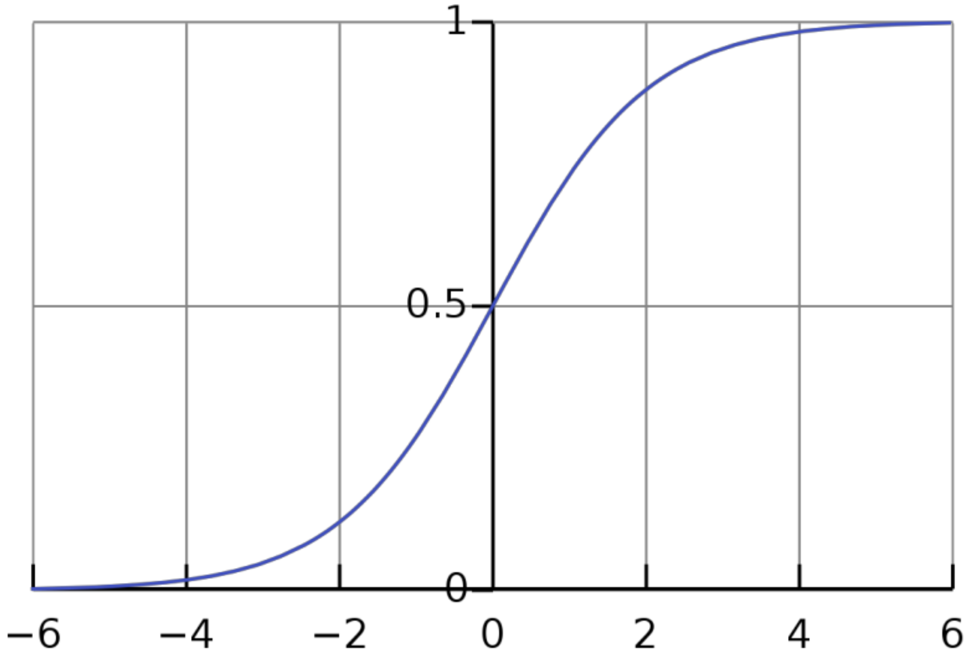

Figure 13: Logistic regression.

4.1.3 Support Vector Machine:

The Support Vector Machine (SVM) is another essential algorithm that every machine learning expert should be familiar with. Many favour SVM because it delivers high accuracy with a relatively low computational cost. SVM can be used for both regression and classification tasks, although it is most commonly applied to classification. The SVM algorithm's primary goal is to find a hyperplane in N-dimensional space that efficiently divides the data points, where N is the number of features. We can use multiple potential hyperplanes to divide the two classes of data. The goal is to find the hyperplane with the maximum margin, meaning the greatest distance between the data points of both classes. By maximising this margin, the model improves its ability to classify future data points with greater reliability.

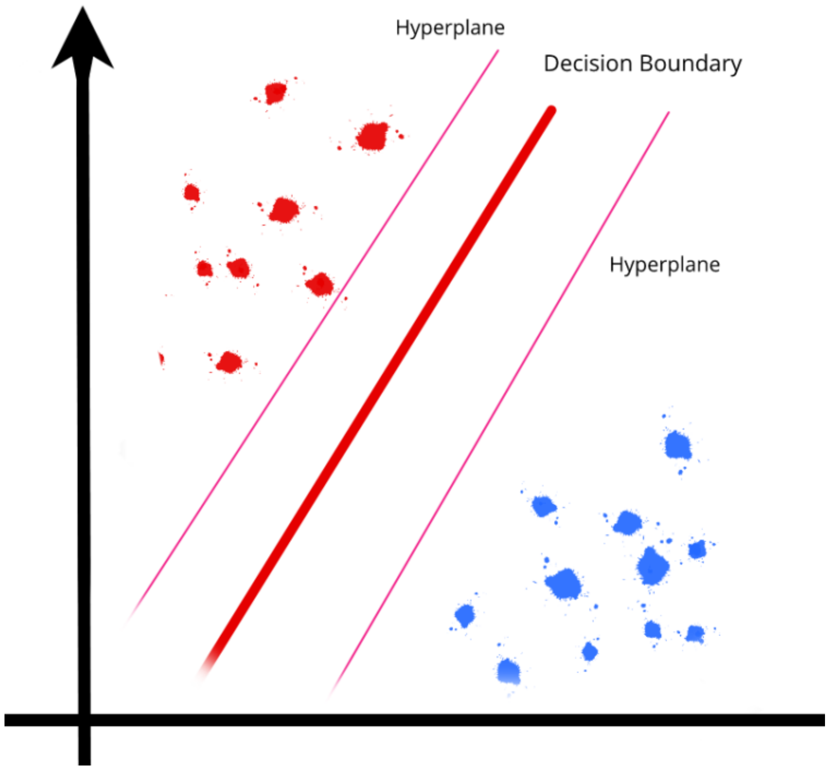

Figure 14: Support vector machine [43].

4.2 Unsupervised learning

Unsupervised learning is the process of analysing and classifying unlabelled datasets using machine learning algorithms. Because these algorithms may find hidden patterns in the data without human input, they are called "unsupervised". [44].Clustering, association, and dimensionality reduction are the three main objectives for which unsupervised learning models are employed.

4.2.1 Clustering

Clustering is a data mining technique employed to categorise unlabelled data according to their similarities or disparities. For instance, K-means clustering algorithms categorise similar data points into clusters, with the value K indicating the number of groups and their level of granularity. This clustering method is useful for various applications, such as market segmentation and image compression [45].

4.2.2 Association rules

constitute an additional category of unsupervised learning that uses various rules to find correlations between variables in a dataset. Recommendation systems and market basket analysis frequently employ these methods, including the "Customers Who Bought This Item Also Bought" suggestions.

4.2.3 Dimensionality

A learning method called "dimensionality reduction" is applied when a dataset has an excessive number of characteristics, or dimensions. While maintaining the data's integrity, it reduces the quantity of data inputs to a more manageable level. This technique is frequently used in the data preprocessing phase, for example, when autoencoders improve image quality by removing noise from visual data. [46].

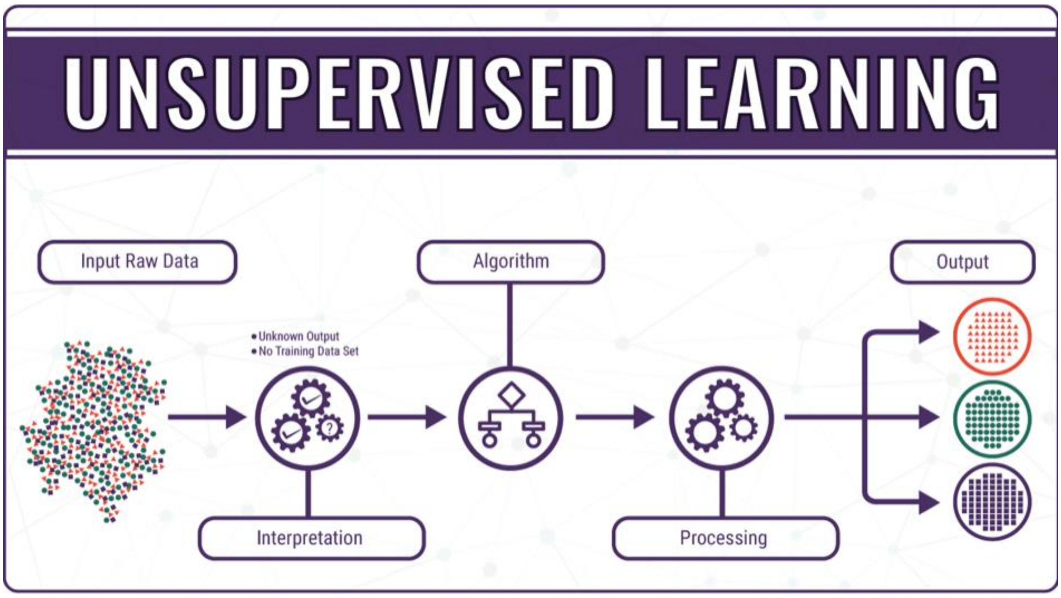

Figure 15: Unsupervised learning [47].

The algorithms used in this approach include:

- K-Means Clustering
- Gaussian Mixture Model

- Hidden Markov Model
- Principal Component Analysis (PCA)

Some applications of unsupervised machine learning are:

- Examining human conduct
- Analysing social networks to find friend groupings
- Company market segmentation based on geography, sector, or vertical
- Clustering computers according to comparable processes and event patterns

4.3 Semi-supervised learning

The dataset includes both structured and unstructured data, which help guide the algorithm in drawing independent conclusions. By combining these two types of data within a single training set, machine learning algorithms can learn to classify unlabelled data. This approach is especially valuable when extracting relevant features from data is challenging or when dealing with large volumes of data.

4.4 Reinforcement learning

Reinforcement learning is a behavioural model of machine learning that, unlike supervised learning, does not rely on pre-labeled sample data. Instead, the algorithm acquires knowledge through a process of experimentation and failure. It strengthens behaviours that lead to positive outcomes and refines its strategy to determine the best recommendation or policy for solving a problem.In reinforcement learning, the system learns to map situations to actions in order to maximise a cumulative reward or reinforcement signal. Unlike other machine learning methods, the learner is not explicitly told which action to take; rather, it must explore different actions to determine which ones lead to the highest rewards. In more complex cases, actions may influence not only the immediate reward but also future situations and rewards. The two key features that define reinforcement learning are its trial-and-error approach and the delayed nature of rewards. [48].

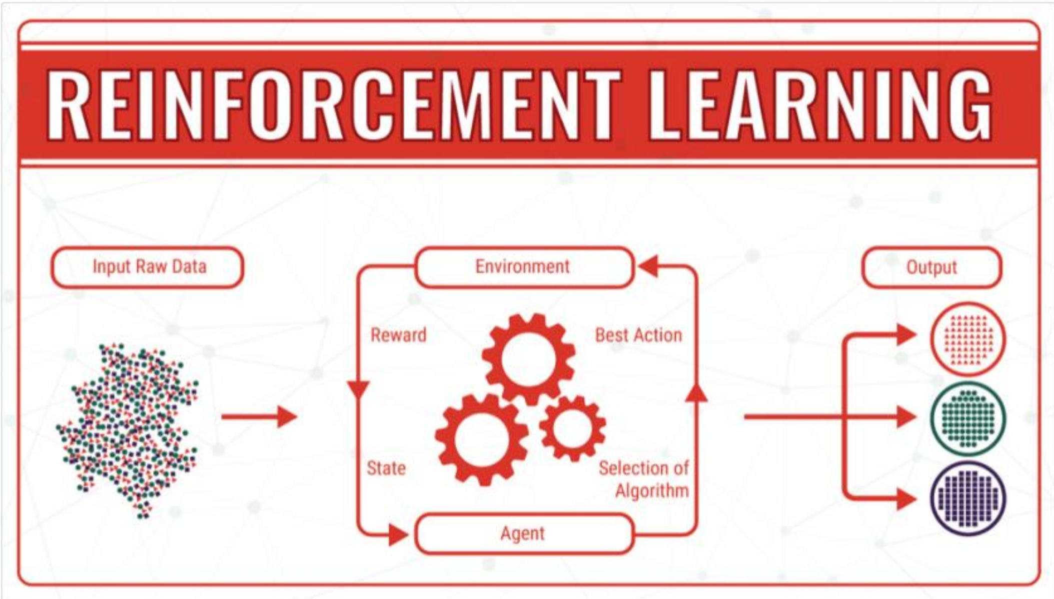

Figure 16: Reinforcement learning.

5 Deep Learning

Deep learning, a subset of machine learning, addresses the feature selection challenge. Also known as hierarchical learning, deep learning identifies subtle patterns in data by applying a learning method, then constructs a mathematical model and integrates it as the final classifier. Its significance lies in the fact that we no longer need to manually search for the optimal features or attributes for each problem; the algorithm handles this process automatically. This is why deep learning has become so influential.

Today, deep learning (DL) has become the dominant approach in machine learning, offering significantly improved pattern recognition and image classification compared to traditional machine learning (ML) methods [49].

6 Neural Network

An artificial neural network is a computational model designed based on the structure and function of neural networks in the brain. Simplified brain models consist of numerous basic computing units (neurones) interconnected within a complex communication network, enabling the brain to perform highly sophisticated computations. Artificial neural networks replicate this computational paradigm as formal constructs. The concept of learning with neural networks emerged in the mid-20th century, offering an effective learning framework that has recently achieved state-of-the-art performance in various tasks [49].

A neural network can be represented as a directed graph where the nodes correspond to neurones, and the edges represent the connections between them. Each neurone processes inputs as a weighted sum of the outputs from connected neurones. This discussion focuses on feedforward networks, a type of neural network with a structure that does not include cycles in its graph representation.

6.1 Activation function

A mathematical function that takes an input and produces an output is called an activation function. It becomes active when the calculated result meets or exceeds a predefined threshold [50].

- **Linear Activation Function:**

  The activation function implies a linear relationship between the inputs and the output by simply scaling an input by a factor. The formula is as follows:

$$\text{Output} = y * x \tag{17}$$

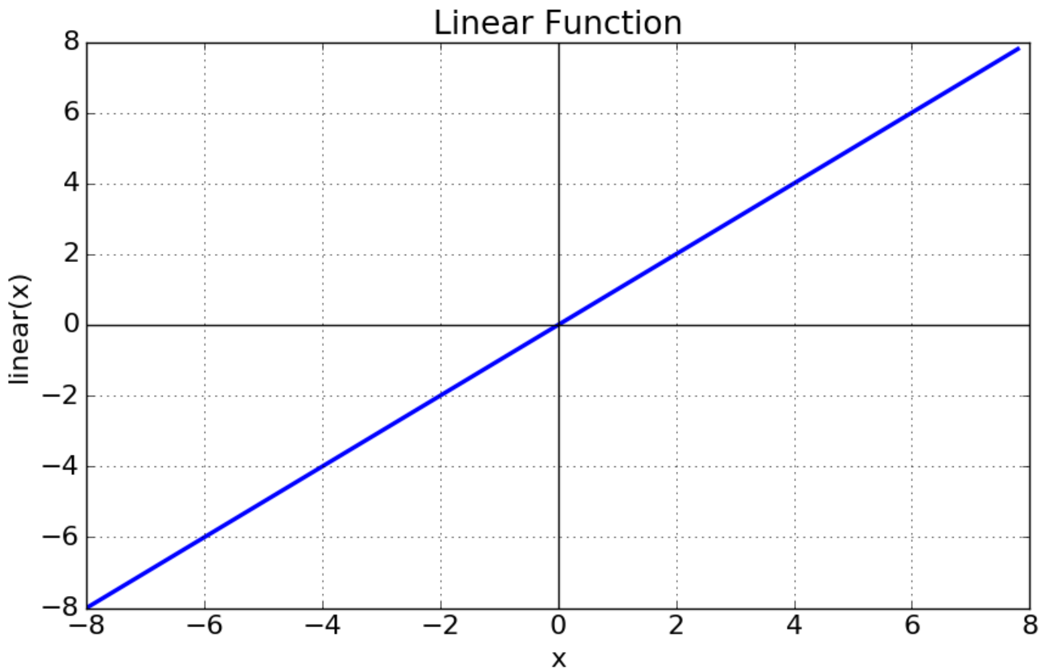

Figure 17: Linear Activation Function.

- **Sigmoid Activation Function:**

  The sigmoid activation function has an "S" shape. It introduces non-linearity to the output and produces a binary result, either 0 or 1.

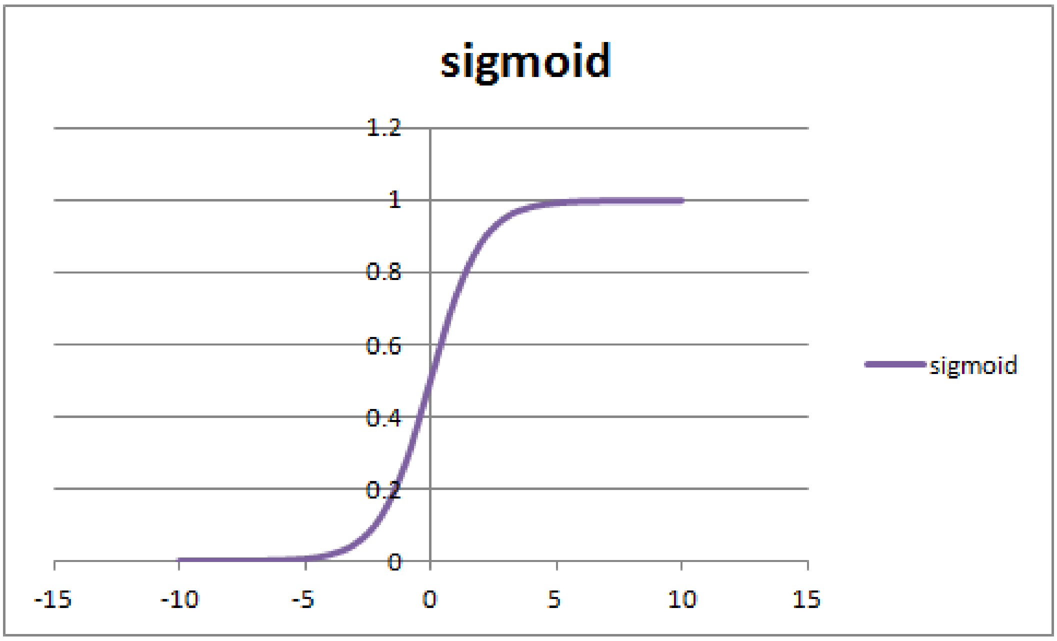

Figure 18: Sigmoid Activation Function.

$$\text{Output} = \frac{1}{1 + e^{-x}} \tag{18}$$

- **Tanh Activation Function:**

  Tanh is an extension of the sigmoid activation function, providing non-linearity to the output. Its output range is from -1 to 1, and it effectively shifts the results of the sigmoid activation function.

$$\text{Output} = \frac{2}{1 + e^{-2x}} - 1 \tag{19}$$

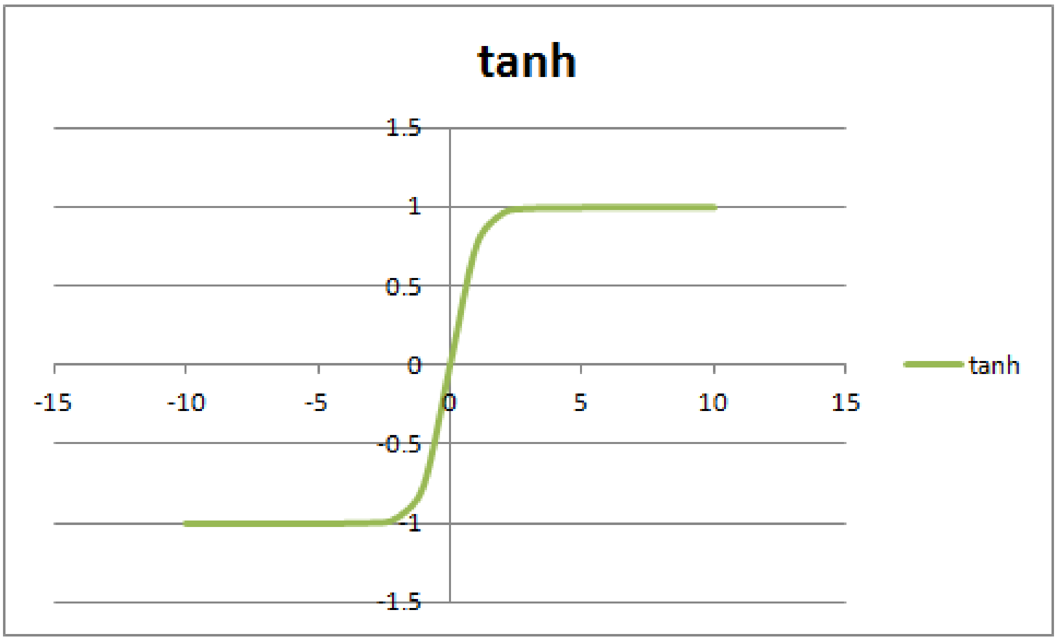

Figure 19: Tanh Activation Function.

- **Rectified Linear Unit Activation Function (RELU):**

  RELU is one of the most commonly used activation functions, especially in hidden layers. Its concept is simple and it introduces non-linearity to the output. The output can range from 0 to infinity.

$$\text{Output} = \max(0, \text{input}) \tag{20}$$

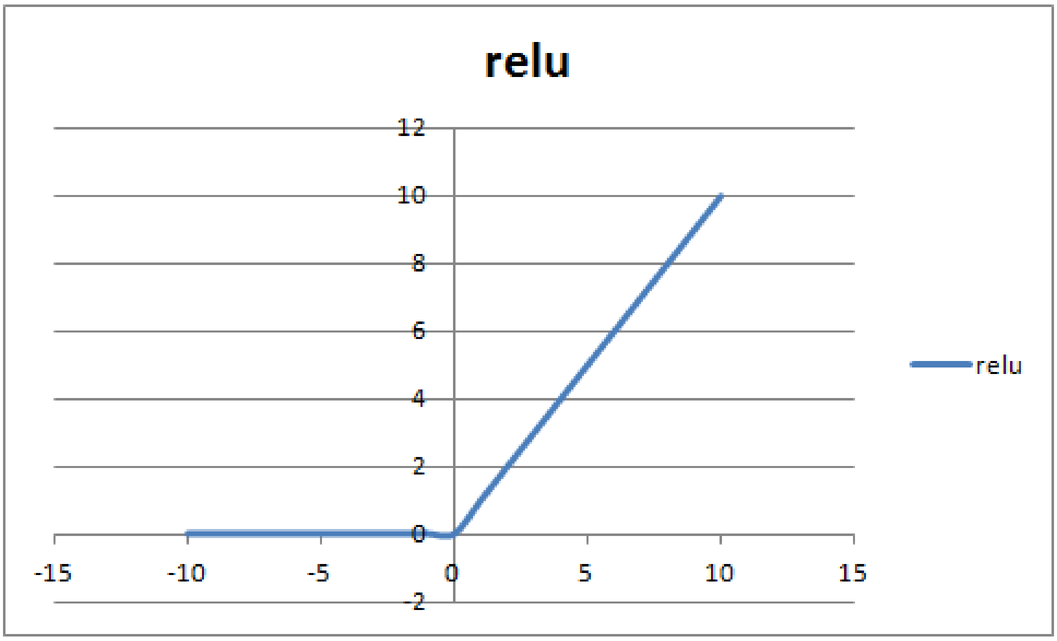

Figure 20: Relu Activation Function.

- **Softmax Activation Function:**

  The Sigmoid activation function is extended by Softmax. It is primarily utilized for classification tasks when it is necessary to compute many classes of results, and it adds non-linearity to the output.

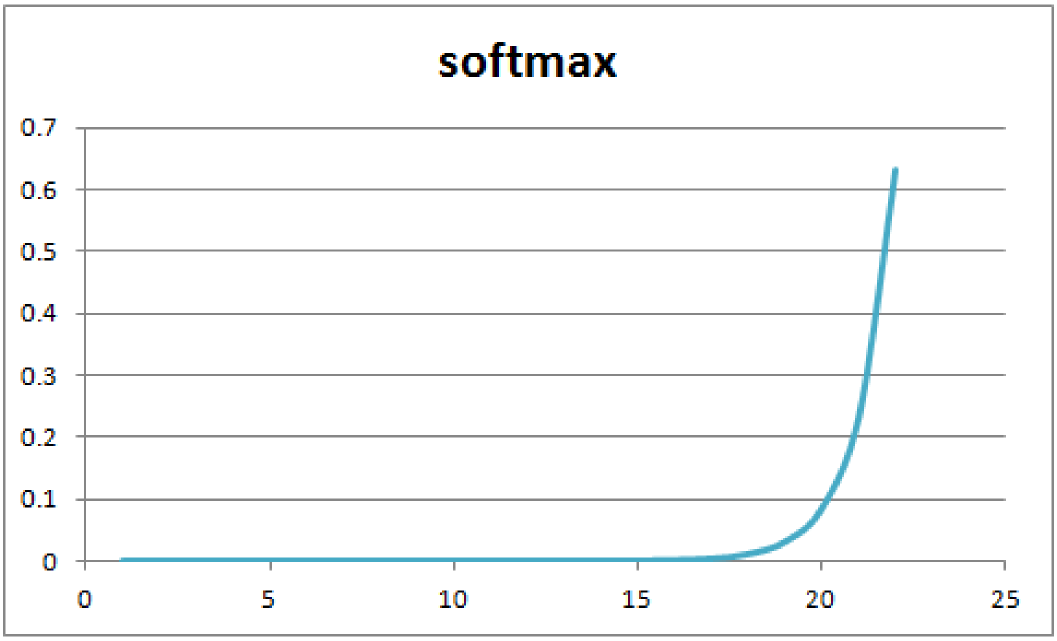

Figure 21: Softmax Activation Function.

6.2 Deep Neural Network Types

Deep Learning consists of three main types, which we will explore in detail:

6.2.1 Artificial Neural Network:

Multiple neurons or perceptrons make up each layer of an artificial neural network (ANN). Due to the fact that the inputs are only processed forward, it is also known as a feed-forward neural network. [49].

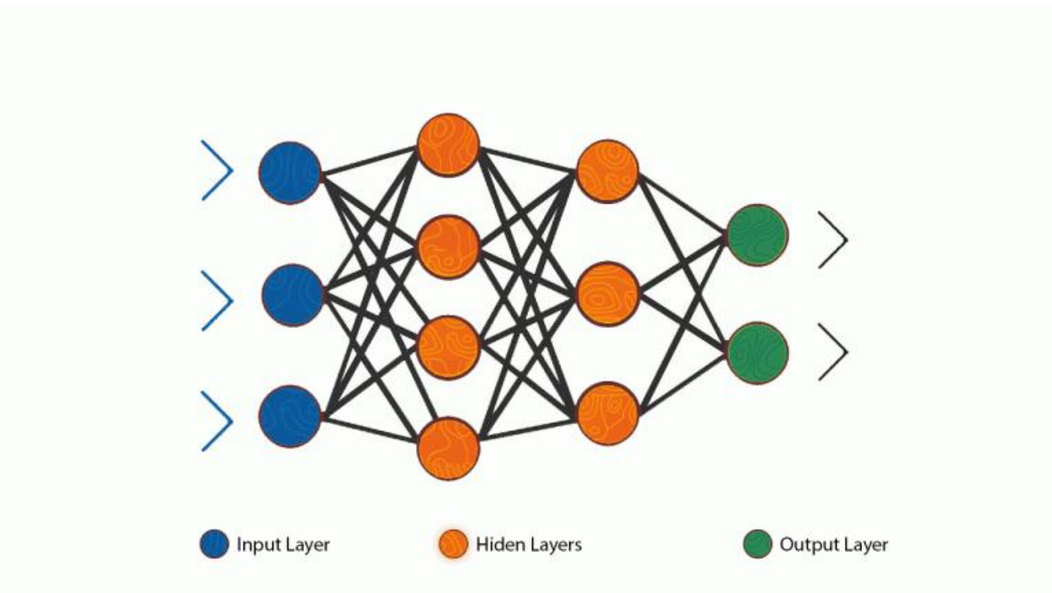

Figure 22: Artificial Neural Network.

The Neural Network is composed of three types of layers:

- **Input Layer:** This is the point at which the neural network acquires the initial data for processing.
- **Hidden Layers:** The input and output layers are separated by these intermediate layers, which are located between them. They perform the computations and transformations required to learn patterns from the data.
- **Output Layer:** This layer generates the final results or predictions based on the processed data from the input and hidden layers.

7 Summarize

This chapter introduced the key concepts of AI and deep learning, explaining their relationship. It explained that deep learning constitutes a subfield of artificial intelligence and that the terms artificial intelligence and machine learning are not synonymous. Furthermore, the chapter outlined the three main categories of AI: working with labelled data (supervised learning), unlabelled data (unsupervised learning), and complex processes that involve both. Finally, it highlighted that deep learning involves many technical terms borrowed from different fields, and while familiar terms might have different meanings in the context of deep learning, understanding these distinctions is crucial.

CHAPTER 4

Comparative analysis of machine learning models to predict rectangular patch antenna dimensions

1 Introduction

The demand for better antennas has grown recently due to advancements in wireless communication systems, which has prompted researchers and designers to use the tools and technologies at their disposal to create more effective and efficient antennas.

Due to the non-linear relationship between factors and antenna size on the one hand, and electromagnetic results from numerous modeling programs on the other [51], the design and optimization process is difficult. In order to overcome these obstacles, antenna designers employed a variety of optimization strategies, such as machine learning [52], particle swarm optimization [53], genetic algorithms [54], and more. In particular, this field is greatly impacted by machine learning, or ML.

Applying various machine learning techniques and models to establish a relationship between the antenna's geometric dimensions and electromagnetic responses produced significant results, making it a very useful and effective tool in addressing the non-linear relationship in this domain. This field is heavily impacted by machine learning (ML).

Non-linear features are retrieved from large datasets by examining the connections between different variables in these problems. Compared to conventional methods, this approach greatly saves designers time and effort by making it easier to predict new inputs based on probabilistic aspects. The traditional method for optimizing antenna parameters is shown in Figure 23.

A key area of artificial intelligence is machine learning, which focuses on developing models and systems that can infer and learn from data to carry out tasks and make decisions on their own without the need for explicit programming.

Unlike traditional programming, it uses pattern recognition and utilization to achieve continuous performance improvement [55]. The differences between a machine learning-based system and a conventional software system are illustrated in Figure 24. The system receives input data and corresponding output data (results) in machine learning (Figure 24-b). It then creates a model (software) that can translate input into output. On the other hand, in traditional software systems (Figure 24-a), we manually identify patterns in the data and then write code (program) to change the data and produce the desired results.

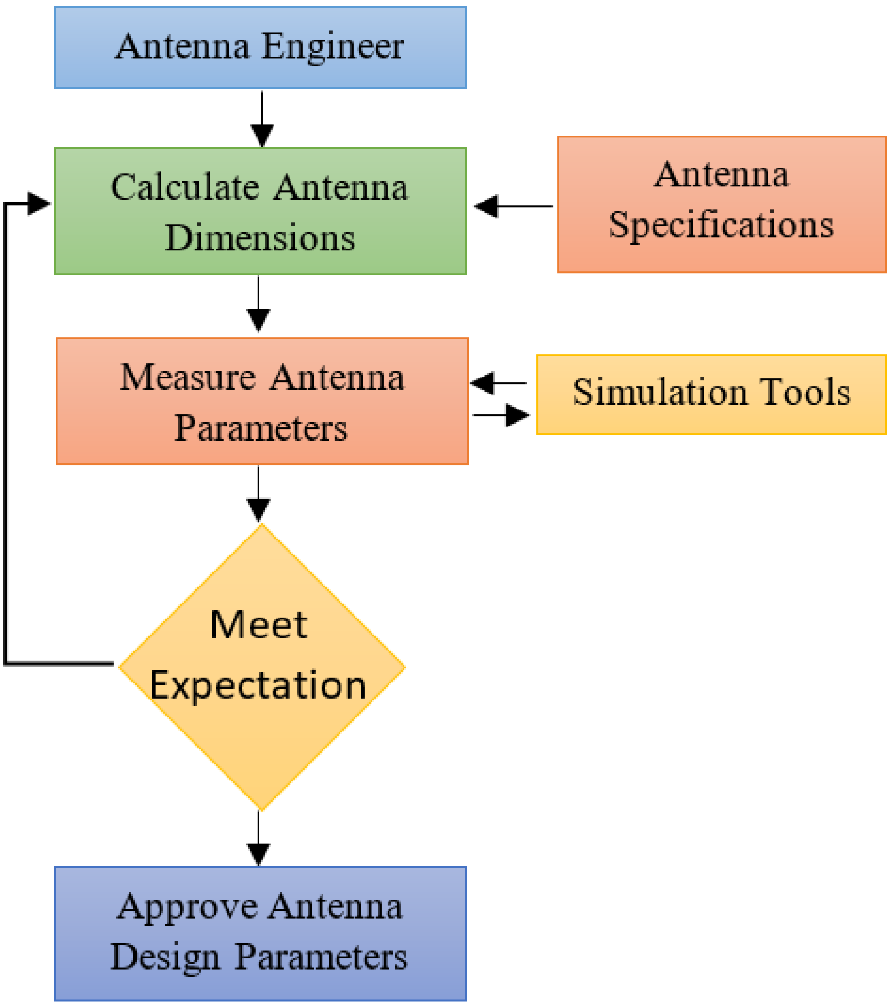

Figure 23: The conventional method for optimizing antenna parameters.

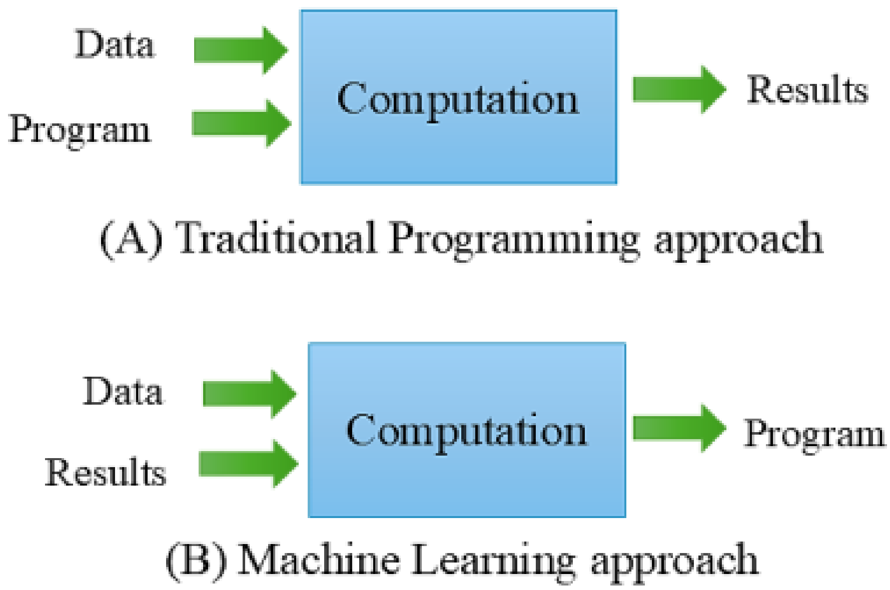

Figure 24: The differences between traditional programming and machine learning [56].

Since the 1990s, the ongoing advancement and application of machine learning in antenna technology has led to promising results, garnering the attention of numerous researchers [57]. Engineers have employed several machine learning techniques in the domain of antennas; this study uses four algorithms, specifically artificial neural networks. [58], support vector regression [59], random forest, and decision tree [60], Regarding the outcomes of these algorithms, the random forest shows exceptional performance. This paper presents a novel methodology for forecasting patch antenna dimensions utilising various machine learning models, including ANN, SVR, random forest, and decision tree, based on a dataset of 3,111 simulated samples obtained through HFSS Simulation software.

2 Antenna structure and dataset

Currently, in contrast to certain other domains, there is no consolidated dataset for microstrip antennas recognised as a reference for academics [61].

Consequently, individuals tend to construct a dataset based on their personal experiences.

A rectangular patch antenna was designed utilising HFSS simulation software version 15.0, a robust tool frequently used in electromagnetic analysis and antenna design. The HFSS, or High-Frequency Structure Simulator, allows engineers and researchers to properly mimic and evaluate electromagnetic behaviour, serving as a crucial tool for forecasting antenna performance in real-world settings. HFSS necessitates a Windows operating system, a minimum of 16 GB of RAM, a multi-core processor, a compatible graphics card, and adequate disc space for installation and data storage. [62].

An antenna, depicted in Figure 25, was constructed to acquire a dataset for the development of machine learning models. The antenna was constructed using a FR-4 substrate, selected for its prevalent application and dependability in PCB fabrication, measuring 60 mm x 60 mm $\times$ 1.6 mm. The substrate thickness measures 1.6 mm, the dielectric constant is $\varepsilon_r = 4.4$, and the loss tangent is $\tan\delta = 0.02$.

The antenna operating frequency was chosen to be 2.45 GHz. This frequency is widely adopted as part of the Industrial, Scientific, and Medical (ISM) band, offering license-free operation in most countries. It is commonly utilized in several modern wireless applications, including Wi-Fi, Bluetooth, RFID, and IoT systems, which makes it a practical and versatile choice. Furthermore, it provides a good trade-off between antenna size and propagation performance, ensuring suitability for compact and efficient designs.

The initial antenna design is illustrated in Figure 25.

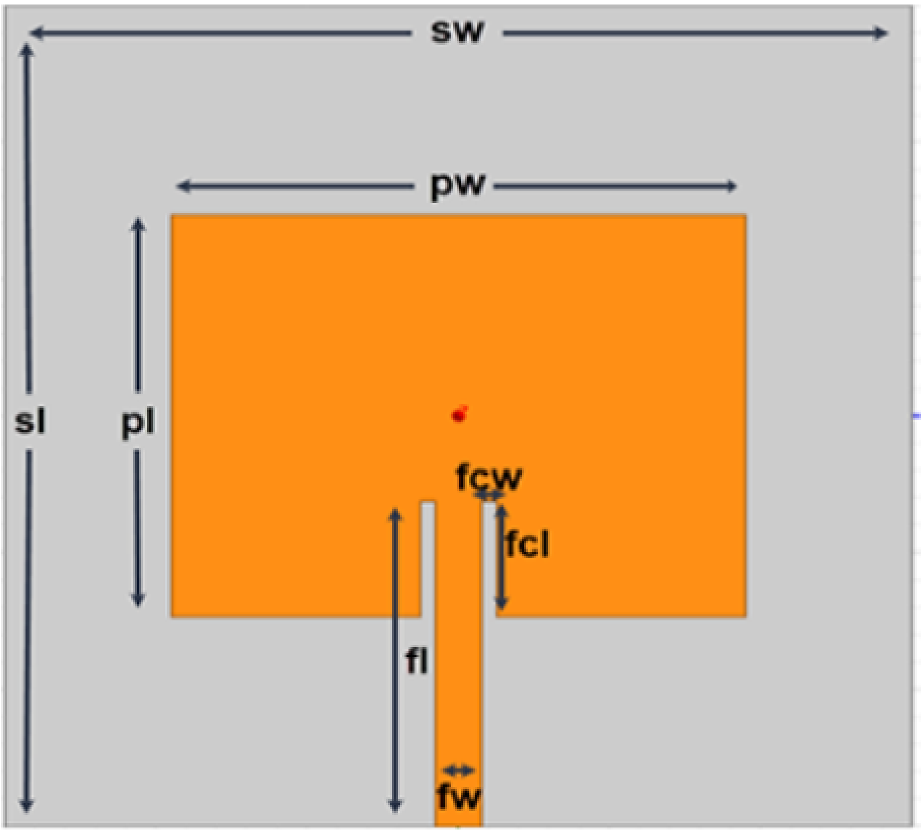

Figure 25: The initial antenna.

3 Initial antenna performance metrics

Figures 26 to 29 depict diverse performance metrics of the preliminary microstrip patch antenna acquired by HFSS software.

3.1 Return loss

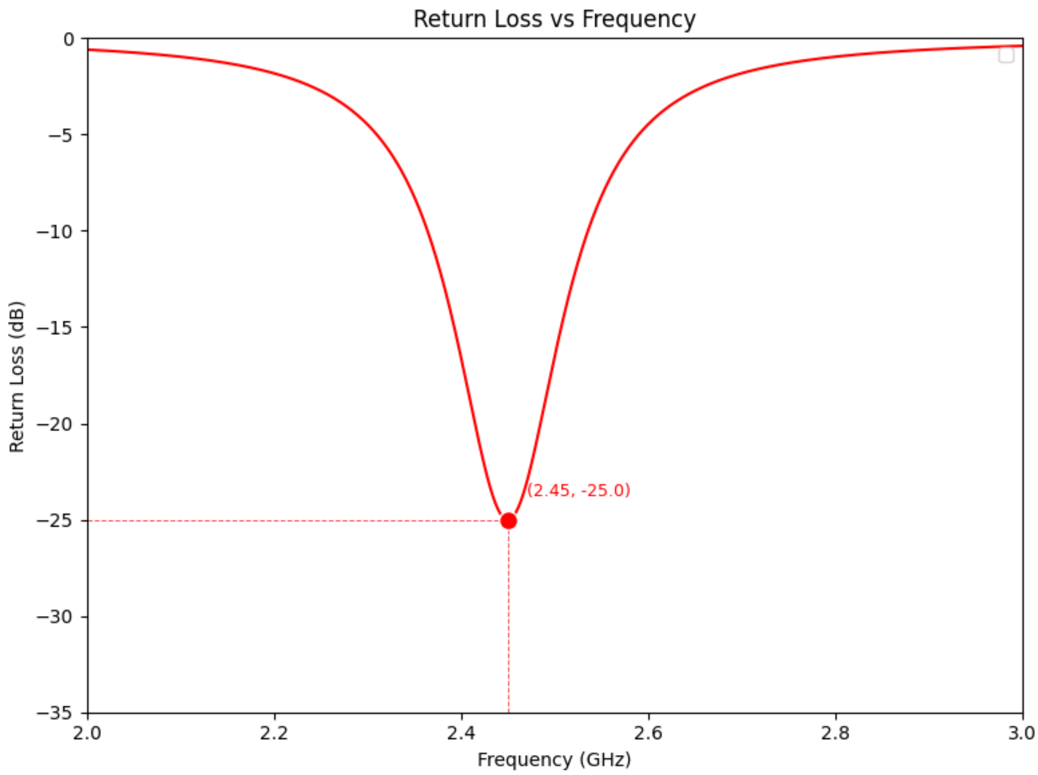

Figure 26: Return loss Vs. Frequency.

Figure 26 illustrates Plot of simulated return loss against frequency for the initial antenna derived from HFSS. The developed antenna has a return loss value of -24.88 dB at a frequency of 2.46 GHz. The substantial return loss at the designated frequency signifies effective impedance matching and good radiation, rendering the antenna exceptionally appropriate for applications functioning at this frequency. The 2.46 GHz resonant frequency is frequently employed in wireless communication technologies, including Wi-Fi, Bluetooth, ZigBee, RFID systems, and medical telemetry. These applications use the antenna's superior efficiency and good performance at this frequency, rendering it suitable for short-range, low-power communication in diverse consumer and industrial equipment.

3.2 Voltage standing wave ratio

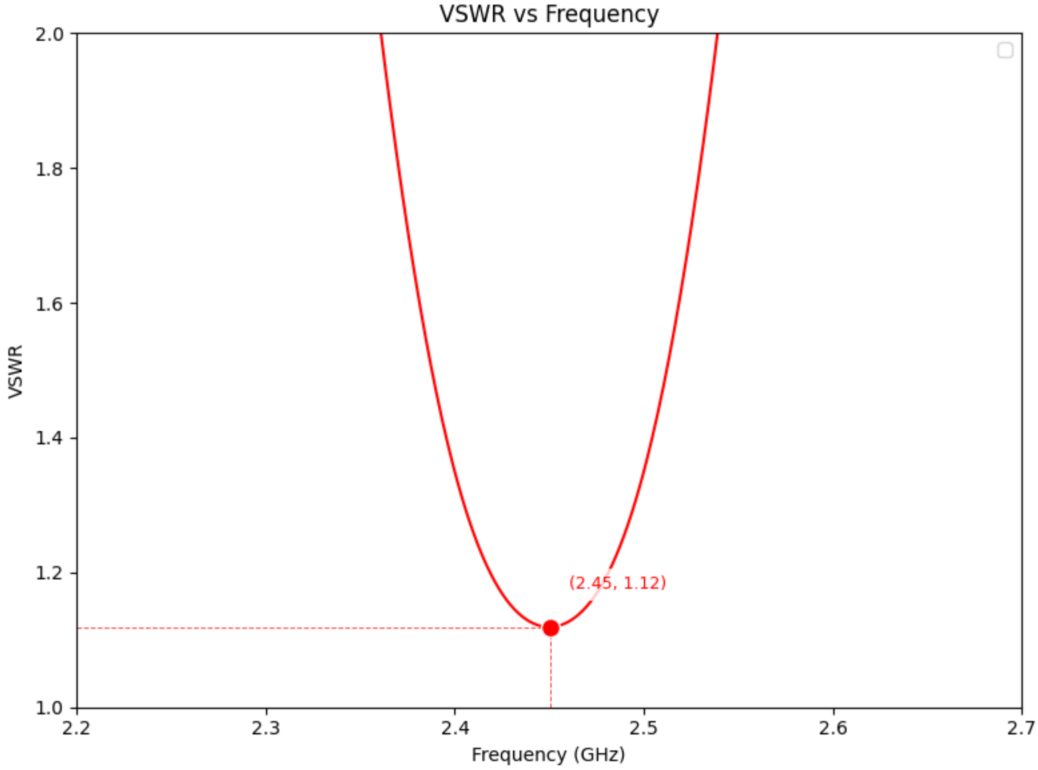

Figure 27: VSWR Vs. Frequency.

The VSWR figure 27 indicates that the VSWR values remain consistently between 1 and 2 over the whole frequency range of the original antenna. This signifies an good impedance alignment between the antenna and the transmission line, facilitating effective power transfer with little reflections. The VSWR value attains its minimum of roughly 1.1208 at a frequency of 2.467 GHz, signifying good matching at this frequency.

Table 2 provides a comparison between Voltage Standing Wave Ratio (VSWR) and Return Loss (in dB)

Table 2: Comparison between VSWR and return loss.

VSWR	Return Loss (dB)	Description
~ 1.1	24.88 dB	Excellent matching,very minimal reflection.
~ 1.2	20 dB	Very good matching, small reflection.
~ 1.5	15 dB	Good matching, noticeable reflection.
~ 2.0	10 dB	Acceptable matching, some reflection.
~ 2.5	6 dB	Poor matching, significant reflection.
$\sim \infty$	0 dB	Total reflection. Open circuit, cut, or no load.

3.3 Gain

Figure 28 displays the three-dimensional radiation pattern of the antenna, exhibiting its gain in various spatial directions. The gain, indicating the antenna's capacity to direct radiated power in a particular direction relative to an isotropic radiator, is represented on a scale where the antenna reaches a maximum value of 2.59 dBi. This value signifies that the antenna exhibits a directional bias, concentrating energy in specific directions, which is essential for applications necessitating targeted communication. The three-dimensional map offers an extensive perspective on the antenna's performance across all spatial orientations, facilitating a clearer comprehension of its overall efficiency and directivity.

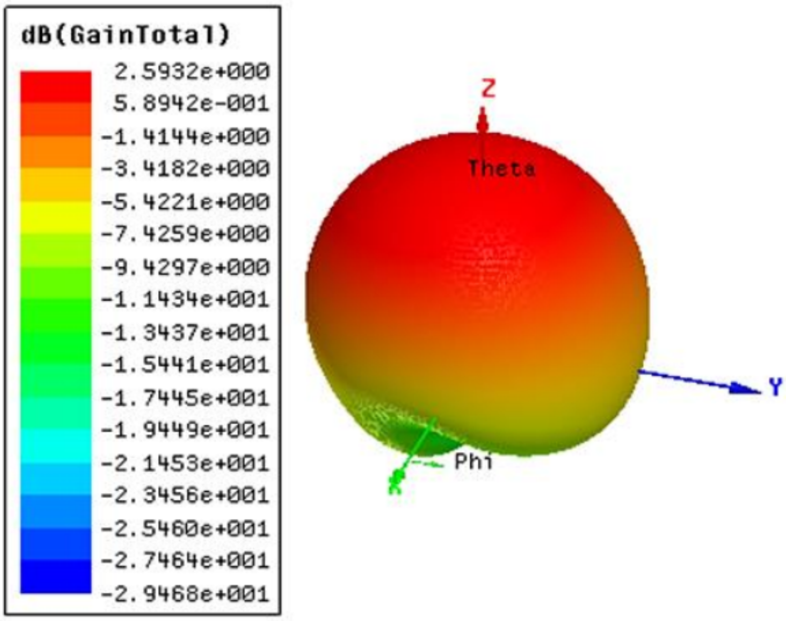

Figure 28: Gain Vs. Frequency.

3.4 Radiation pattern

Figure 29 presents the two-dimensional polar plot of the antenna radiation pattern, providing a cross-sectional representation of the gain at designated planes. The radiation pattern is crucial for understanding how the antenna radiates energy in specific directions relative to its design. The red line in this plot denotes the radiation pattern at an azimuth angle of 0 degrees, whereas the violet line depicts the radiation pattern at an azimuth angle of 90 degrees. This polar plot facilitates the visualisation of the antenna's directional characteristics in distinct planes, illustrating the variation of gain with angle in each instance. The disparities between the red and violet lines underscore the anisotropic characteristics of the radiation, indicating that the antenna's performance fluctuates based on its orientation.

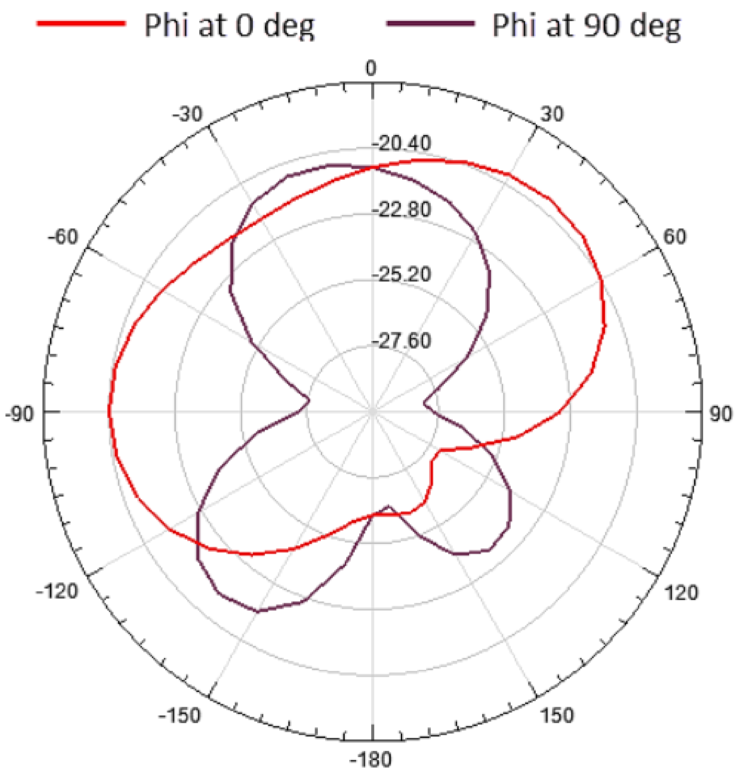

Figure 29: A two-dimensional radiation pattern (at phi=0, phi=90 degrees).

4 Comparative analysis of ML models to predict MPA dimensions

Building upon the initial antenna design, this section explores the potential for improving the antenna's design using machine learning (ML) models. The focus is on leveraging the power of ML algorithms to optimise the initial antenna based on its electromagnetic performance metrics. By analysing the existing antenna data and applying advanced ML techniques, we aim to refine the antenna design while enhancing its efficiency and performance. The goal is to explore the advantages of using predictive models to inform design adjustments, optimising the antenna's capabilities while reducing the need for time-consuming iterative simulations and experiments.

4.1 Dataset collection

A dataset of 3111 rows was obtained by varying the patch width from 26 to 31 mm in increments of 0.1 mm and the patch length from 35 to 41 mm in increments of 1 mm to generate diverse design combinations. This dataset was preserved in a tabular format within a CSV (comma-separated values) file. The table comprises five columns: patch length, patch width, frequency, bandwidth, and S11. The other variables were held constant to simplify the task. The various design parameters are enumerated in Table 3.

Table 3: Parameters of antenna.

Parameter	Description	Value
Pl	Patch length	35mm to 41mm
Pw	Patch width	26mm to 31mm
Sw	Substrate Width	60mm
Sl	Substrate length	60mm
Fl	Feed length	23.8mm
Fw	Feed width	3.1mm
Fcw	Feed cut width	0.95mm
Fcl	Feed cut length	8.5mm
h	Substrate height	1.6mm

The dataset was partitioned into two segments: the initial segment comprises 80% of the data for model training, and the subsequent segment consists of 20% of the data for testing purposes. This split follows the recommendations in [63], ensuring that the models were trained on most of the data while being tested on new examples.

4.2 Machine Learning Algorithm Implementation

After collecting the dataset, we used machine learning methods to predict the antenna dimensions according to specified performance parameters. This study selected SVR, random forest, ANN, and decision tree algorithms due to their proficiency in managing prediction jobs well.

Figure 30 illustrates the various stages involved in constructing artificial intelligence (AI) models for predicting the antenna's length and width. The procedure commences with the ingestion of the dataset, thereafter partitioning it into two segments: 80% allocated for training and 20% for testing. The aforementioned models are subsequently trained on the training data. Upon completion of the training, the subsequent stage involves generating predictions utilizing the testing data. The outcomes are assessed by computing the mean squared error between the actual data and the model's predictions.

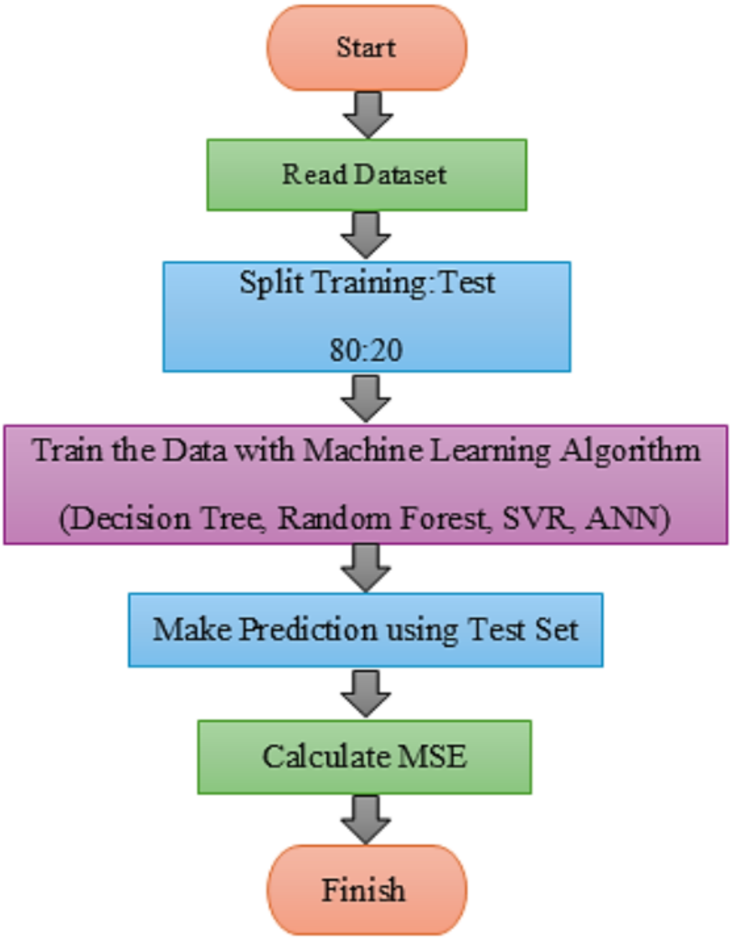

Figure 30: Different processes of creating an artificial intelligence model.

4.2.1 Evaluation metrics

The models employed in this study can be assessed using the following criteria:

Loss function

In regression analysis, the loss function is a mathematical formulation that measures the divergence between predicted values and actual values. A diminished loss function value signifies enhanced forecasting accuracy. Numerous loss functions are available for regression analysis, each with unique benefits and drawbacks. Among the most prevalent loss functions are:

4.2.2 Mean Squared Error (MSE)

It is a statistic employed to evaluate the accuracy of a predictive model. The calculation involves averaging the squared deviations between the observed and expected values. The model exhibits greater accuracy when the MSE is minimized [63]. We use the following equation to calculate the model:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{21}$$

4.2.3 Root Mean Square Error (RMSE)

It quantifies the average magnitude of the discrepancy between expected and actual values. The calculation entails determining the square root of the mean of the squared variances between the anticipated and actual values. A reduced RMSE indicates a better fit of the model to the data. MSE indicates the magnitude of the mistakes produced by our model [63]. We use the following formula for the calculation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{22}$$

4.2.4 Mean absolute error (MAE)

It is a metric that quantifies the average absolute deviation between expected and actual values. The computation entails ascertaining the absolute value of the disparity between each anticipated value and its corresponding actual value, thereafter averaging these absolute disparities. A lower MAE indicates a superior fit of the model to the data [64]. MAE can be calculated using Equation 23:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{23}$$

4.3 Results

This section presents the MSE results obtained for each algorithm.

4.3.1 Random forest MSE result

Figure 31 illustrates that the MSE value progressively decreases as the number of estimators increases from 0.61 to 0.53, stabilizing at 60 and reaching its minimum value of 0.52 at 100 estimators.

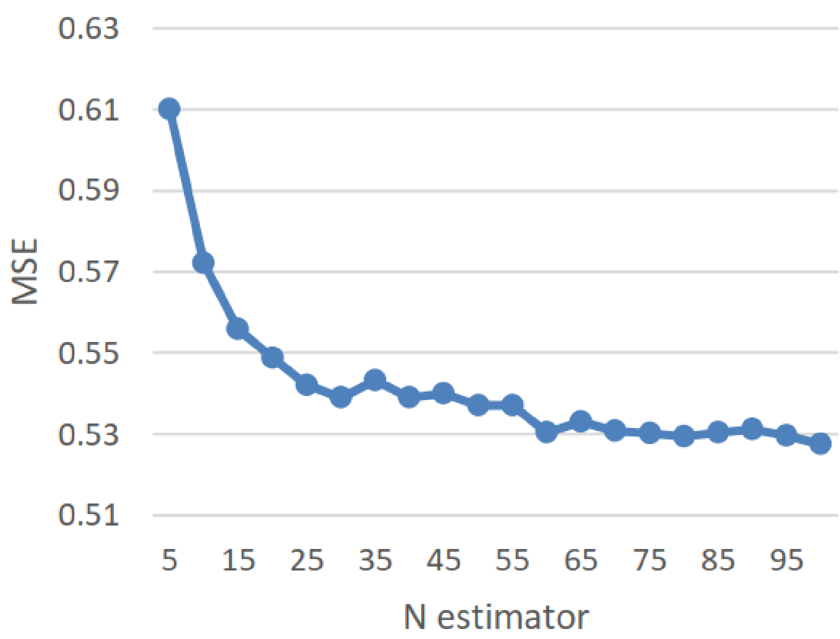

Figure 31: Random forest MSE result.

4.3.2 SVR

Figure 32 depicts the mean squared error (MSE) for different values of epsilon and gamma. Employed to improve the predicted outcomes. Epsilon delineates the permissible margin of error, while gamma elucidates the influence of the acquired data. When gamma equals 0.1, the mean squared error (MSE) is roughly 0.65. When gamma is 0.01, the mean squared error (MSE) is around 16. When gamma is 0.001, the mean squared error (MSE) approximates 0.87. When gamma is set to 0.01, the mean squared error (MSE) is approximately 1.05. Ultimately, with gamma set at 0.0001, the mean squared error (MSE) approximates 1.95. Thus, it can be concluded that gamma significantly affects the prediction results. As the gamma parameter increases, the MSE value proportionately escalates. Altering the epsilon value does not yield as substantial a difference as adjusting gamma. Thus, it may be concluded that the epsilon parameter improves the predicted outcome. The minimal mean squared error is achieved when gamma is set to 0.1 and epsilon is configured to 0.1.

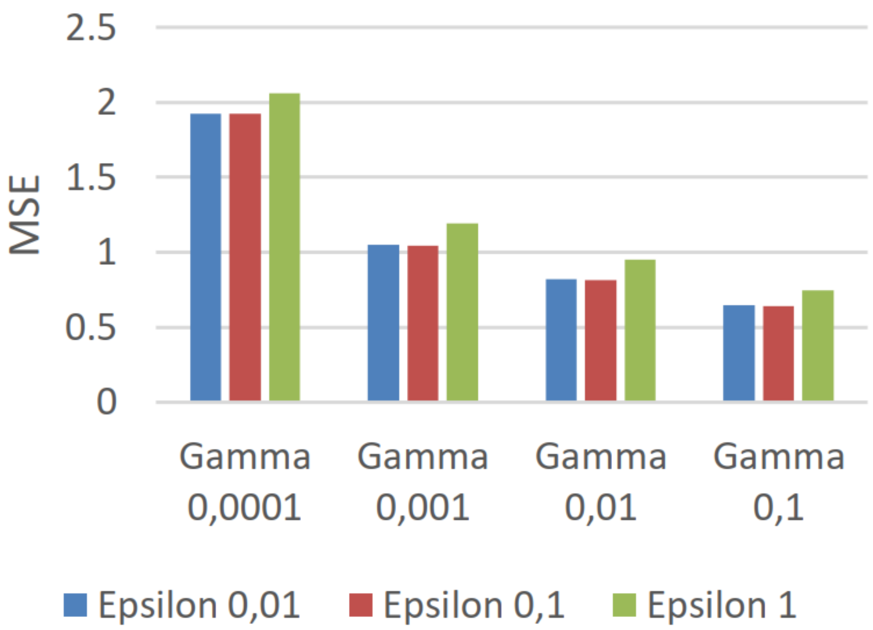

Figure 32: SVR MSE result.

4.3.3 Decision tree

Figure 33 depicts the MSE values across several random states. The MSE diminishes as the random state increases from 0 to 5, varying from 0.65 to 0.60. Unfortunately, the MSE increases until it attains a value of 0.73 when the random state is set to 25. Subsequently, it fluctuates until the random state attains 35. The mean squared error attains its minimum when the random state is configured to 5. The variable outcome arises from the intrinsic characteristics of the random state, which randomly selects the data.

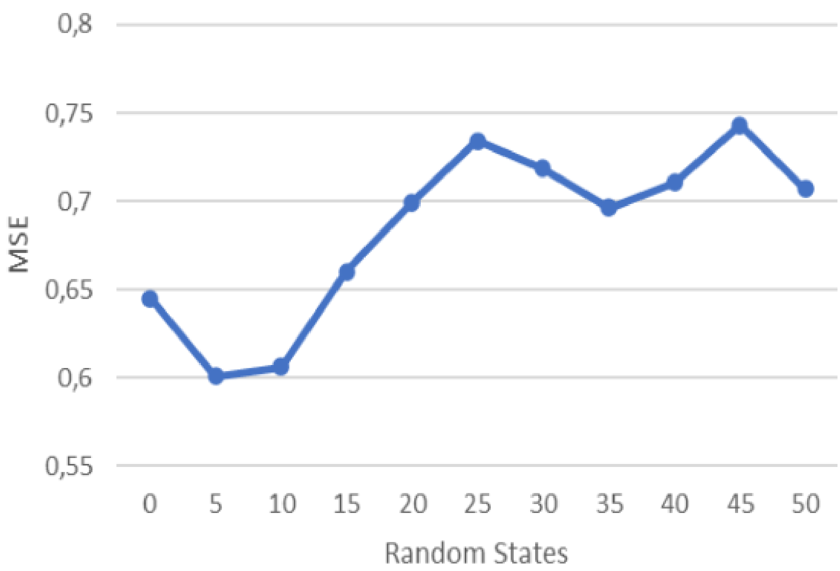

Figure 33: Decision tree MSE result.

4.3.4 ANN

The reduction in the MSE value correlates with the increase in the number of hidden layers, achieving its minimum at six layers, followed by subsequent fluctuations, as illustrated in Figure 34.

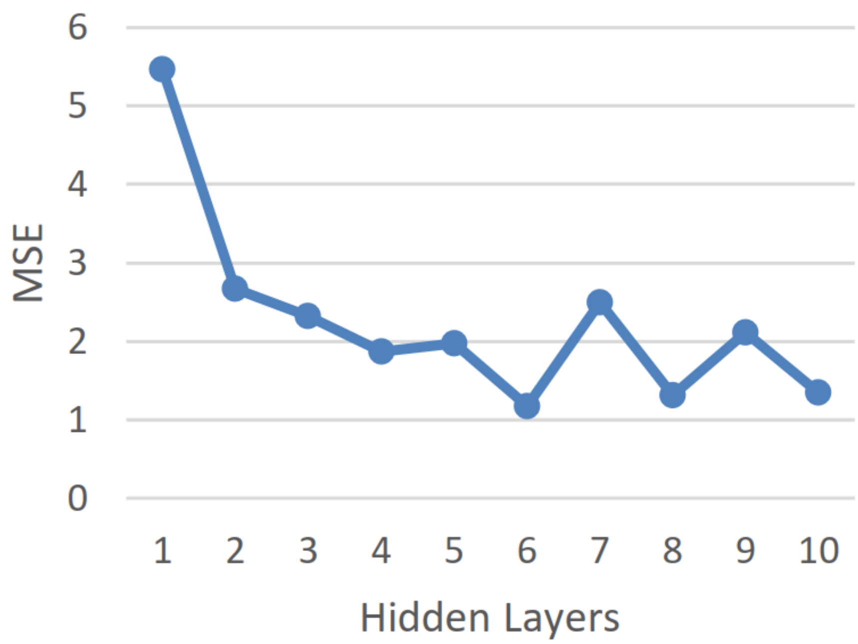

Figure 34: ANN MSE result.

4.4 Result comparison

The best prediction outcomes derived from the four methods are presented in Table 4 along with their parameters.

Algorithm	Parameter	MSE
ANN	Hidden layers 6	1.17
Decision Tree	Random state 5	0.6
Random Forest	N-estimator 100	0.52
SVR	Gamma 0.1, Epsilon 0.1	0.64

Table 4: Best results obtained

Table 4 indicates that the ANN method attains the minimum MSE of 1.17 with six hidden layers. The decision tree approach records its lowest MSE of 0.6 at random state 5, while the random forest achieves an MSE of 0.52 with 100 estimators. The final MSE value of 0.64 for the SVR algorithm is attained with a gamma of 0.1 and an epsilon of 0.1. Of all the algorithms, the random forest approach demonstrated superior efficacy in predicting the antenna dimensions.

4.5 Inverse modeling of patch antenna dimensions using machine learning

Traditionally, machine learning models are used to predict the performance metrics of an antenna, such as resonant frequency, bandwidth, and return loss, based on known geometric parameters. However, in this study, an inverse modeling approach is adopted, where the desired electromagnetic performance metrics are provided as inputs to the model, and the outputs are the physical dimensions of the antenna, namely the patch length (Pl) and patch width (Pw).

This approach is particularly beneficial in antenna design, as it enables rapid estimation of antenna geometry based on specific design requirements without relying on iterative electromagnetic simulations. By learning the complex inverse relationship from performance to geometry, machine learning models can serve as efficient design tools in real-world scenarios.

The input features used for training the inverse models are:

- Resonant frequency (f_r) in GHz
- Bandwidth (BW) in MHz
- Return loss (S11) in dB

The target outputs (labels) are:

- Patch length (Pl) in mm
- Patch width (Pw) in mm

The previous dataset of 3111 samples was used for this purpose, each corresponding to a unique antenna configuration simulated using HFSS. Each sample includes the three performance metrics as inputs and the corresponding patch dimensions as outputs.

The inverse prediction task uses Random Forest as a machine learning algorithm. This model was trained and tested following an 80%–20% data split. Model performance was evaluated using standard regression metrics such as mean squared error (MSE) and mean absolute error (MAE). The results obtained from the model are discussed in detail.

This inverse modeling facilitates the design of the optimized rectangular patch antenna that meets specific performance criteria, thus significantly reducing the need for time-consuming trial-and-error simulations and accelerating the antenna development process.

4.5.1 Optimized design of the initial antenna

After performing the reverse process using the Random Forest model, Table 5 shows the final dimensions of the optimized antenna.

Table 5: The final dimensions of the optimized antenna.

Parameter	Description	Value
Pl	Patch length	37.7mm
Pw	Patch width	27.6mm
Sw	Substrate Width	60mm
Sl	Substrate length	60mm
Fl	Feed length	23.8mm
Fw	Feed width	3.1mm
Fcw	Feed cut width	0.95mm
Fcl	Feed cut length	8.5mm
h	Substrate height	1.6mm

- Return loss (S11)

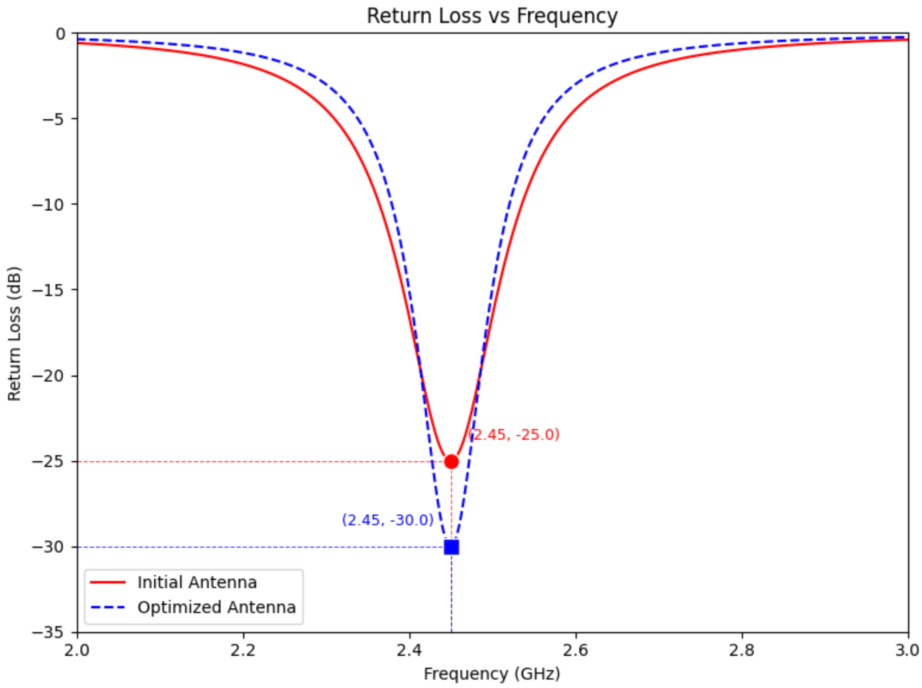

Figure 35: Return Loss Vs. Frequency.

The optimized antenna shows a better performance, as evidenced by the initial S11 results. The return loss reaches approximately -30 dB at a resonant frequency of 2.45 GHz, indicating excellent impedance matching and highly efficient radiation characteristics. Furthermore, the antenna exhibits a -10 dB bandwidth extending from 2.379 GHz to 2.520 GHz, corresponding to a total bandwidth of around 141 MHz. This frequency range lies entirely within the globally allocated 2.4 GHz ISM band, making the antenna highly suitable for integration into modern wireless communication systems. Specifically, it supports widely adopted technologies such as Wi-Fi (IEEE 802.11b/g/n), Bluetooth and Bluetooth Low Energy (BLE), and Zigbee (IEEE 802.15.4), which all operate efficiently within this spectrum. These findings confirm that the optimized antenna not only enhances return loss performance but also provides a practical and reliable solution for compact, low-power, and high-frequency wireless applications.

- VSWR

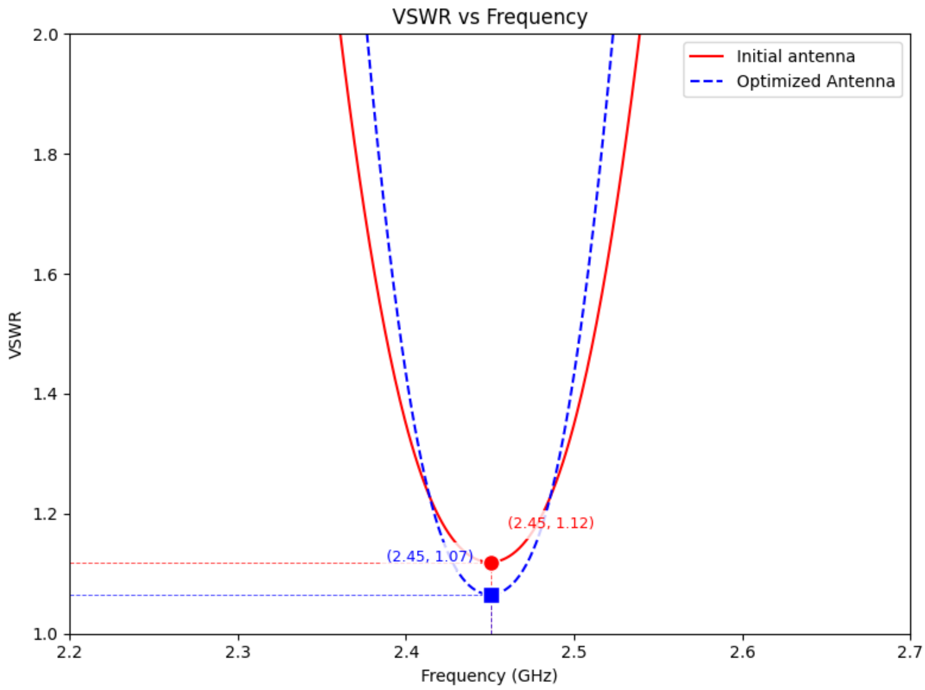

Figure 36: VSWR Vs. Frequency.

Both the initial and optimized antennas demonstrate excellent impedance matching around 2.46 GHz, with VSWR values that remain under 2, which is ideal for most antenna applications. The performance of the optimized antenna appears to be better, with a sharper minimum VSWR. The data indicates that the optimized antenna might offer more efficient power transfer and reduced reflection in comparison to the initial antenna, making it a solid choice for improved performance in this frequency range.

5 Summarize

Chapter 4 provides a comprehensive comparative analysis of various machine learning models used to predict the dimensions of rectangular patch antennas. The chapter starts by explaining the antenna design and the data used, then it defines important performance measures like return loss, voltage standing wave ratio (VSWR), gain, and radiation pattern. We collected and preprocessed the dataset to train the machine learning models. Four algorithms—Random Forest, Support Vector Regression (SVR), Decision Tree, and Artificial Neural Networks (ANN)—were used and assessed based on performance measures like Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

The comparative analysis highlights the strengths and limitations of each model, with Random Forest emerging as the most effective ML model for inverse prediction of patch antenna dimensions, significantly reducing reliance on iterative simulations. Its superior performance (lowest MSE: 0.52) and robustness in handling non-linear relationships were validated against SVR (MSE: 0.64), ANN (MSE: 1.17), and decision tree (MSE: 0.60). These insights demonstrate the suitability of machine learning algorithms for antenna design, particularly in inverse modeling scenarios where geometric parameters are derived from desired electromagnetic responses.

Conclusion

In this thesis, the integration of microstrip patch antennas (MPA) with machine learning (ML) techniques is explored to improve both the design process and prediction accuracy of rectangular patch antennas. The research begins with a comprehensive examination of microstrip antennas, detailing their historical development, feeding techniques, analytical methods, and the key performance metrics that define their functionality. This foundational understanding of antenna theory sets the stage for the main objective of the thesis: applying machine learning algorithms to predict antenna dimensions more efficiently.

Traditional methods for determining antenna dimensions have relied heavily on time-consuming simulations and iterative experimental techniques. This research proposes machine learning as a powerful tool to predict the geometric dimensions of rectangular patch antennas, specifically their patch length and patch width, based on their desired electromagnetic performance. The study applies four widely recognized machine learning models—Random Forest (RF), Support Vector Regression (SVR), Decision Trees, and Artificial Neural Networks (ANN)—to assess their predictive capabilities in antenna design.

The results of this study demonstrate the significant potential of machine learning in enhancing the accuracy of antenna dimension prediction, offering a far more efficient and reliable alternative to conventional methods. Among the tested algorithms, Random Forest exhibited the best performance, achieving the lowest Mean Squared Error (MSE) of 0.52, followed by SVR, ANN, and Decision

Trees. The comparative analysis of these models revealed their individual strengths and weaknesses, offering valuable insights for guiding future antenna design methodologies.

To evaluate the effectiveness of each model, several performance metrics were employed, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). These metrics demonstrated the robustness of machine learning models, with Random Forest particularly excelling in handling non-linear relationships within the data, making it the most effective tool for predicting antenna dimensions based on performance criteria such as resonant frequency, bandwidth, and return loss.

Furthermore, the study introduces the concept of inverse modeling, where the desired electromagnetic performance metrics (such as return loss and resonant frequency) are used as inputs to predict the corresponding antenna dimensions. This approach not only reduces the reliance on lengthy iterative simulations but also accelerates the overall design process, making antenna optimization more accessible and less resource-intensive.

The thesis concludes by highlighting the transformative potential of machine learning in revolutionizing the antenna design process. By leveraging machine learning models, antenna designers can achieve faster, more accurate, and more efficient solutions, which could significantly reduce design time and costs in practical applications. The research suggests that the incorporation of larger datasets, more complex antenna structures, and advanced learning techniques could further improve model performance and expand its applicability.

Ultimately, this research contributes to the ongoing evolution of antenna design and optimization in modern communication systems, underscoring the potential for machine learning to address longstanding engineering challenges. It paves the way for future work in the integration of intelligent systems in antenna design, where more sophisticated algorithms and optimization techniques can enhance antenna capabilities for a wide range of communication technologies.

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