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Theme

**Design and Optimization of Miniature Antennas for
Biomedical Applications Using Artificial Neural
Networks**

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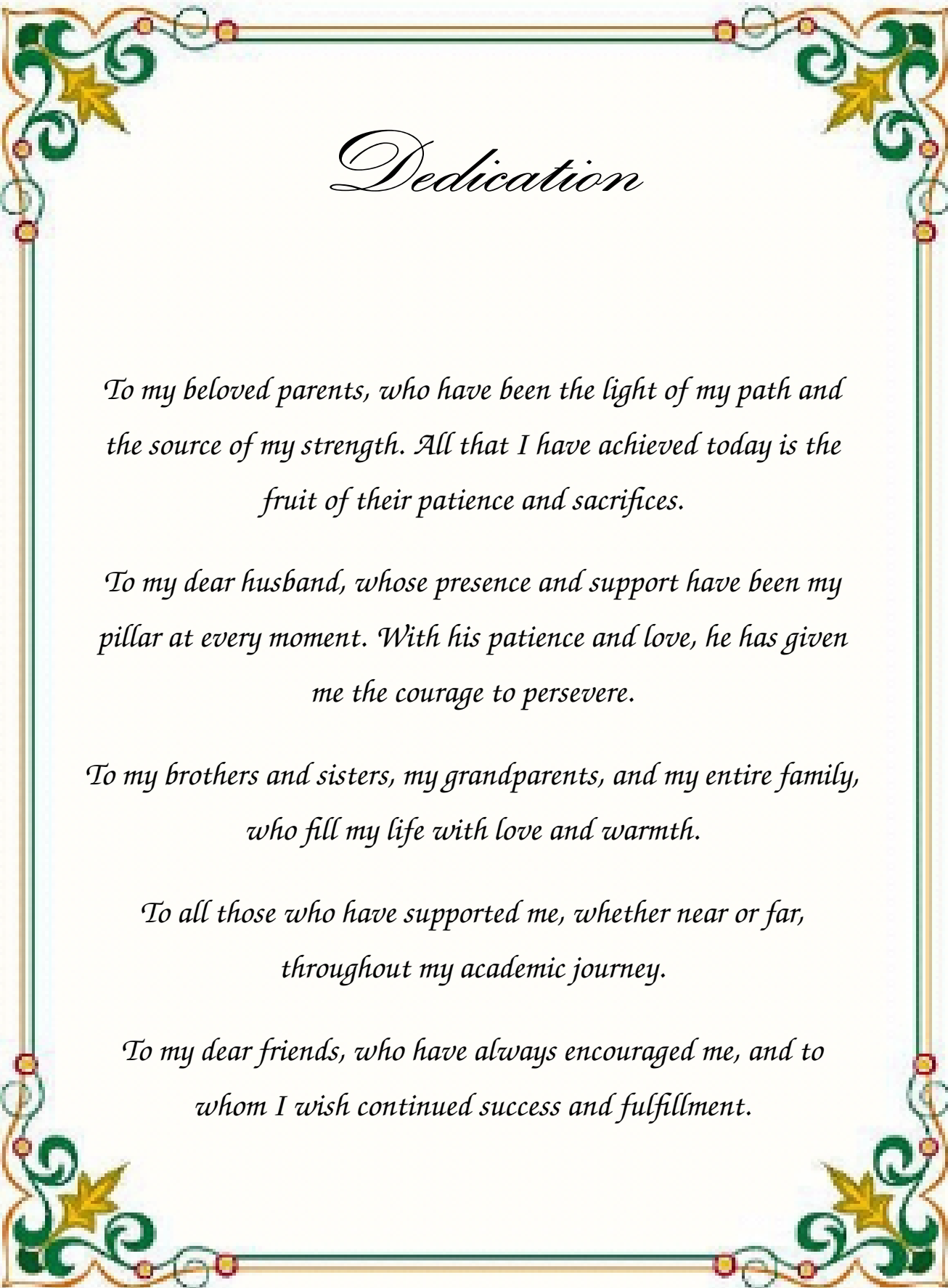
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Dedication

To my beloved parents, who have been the light of my path and the source of my strength. All that I have achieved today is the fruit of their patience and sacrifices.

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ملخص

تلعب الهوائيات الطبية الحيوية دوراً أساسياً في التقنيات الحديثة للرعاية الصحية، إذ تُمكن من تحقيق الاتصال اللاسلكي الموثوق للأجهزة المزروعة داخل الجسم، والمستشعرات القابلة للارتداء، وأنظمة الطب عن بُعد. وتتطلب هذه الهوائيات حجماً صغيراً، وكفاءة إشعاعية عالية، وامتثالاً صارماً لمعدل الامتصاص النوعي لضمان التشغيل الآمن داخل جسم الإنسان. يقدم هذا البحث منهجية متقدمة تعتمد على الشبكات العصبية الاصطناعية العكسية مدمجة مع أسلوب التحسين متعدد الأهداف بهدف تحسين عملية تصميم الهوائيات الطبية الحيوية. تتيح الطريقة المقترحة إمكانية التنبؤ المباشر بأبعاد الهوائي انطلاقاً من الخصائص والأداء المطلوبين، مما يؤدي إلى تقليص كبير في زمن المحاكاة مع الحفاظ على دقة عالية في النتائج. وقد تم تطبيق هذه المنهجية على حالات دراسية تشمل تصميم وتحسين هوائيات النطاق الواسع جداً، وهوائيات النطاق المزدوج الخاصة بتطبيقات النطاقات الصناعية والعلمية والطبية، حيث أظهرت النتائج فعالية النماذج المقترحة في تحقيق التصغير، وتحسين مطابقة المعاوقة، وتقليل معدل الامتصاص النوعي.

كلمات مفتاحية: الهوائي الطبي الحيوي، معدل الامتصاص النوعي، التصغير، الشبكات العصبية الاصطناعية العكسية، التحسين متعدد الأهداف، الهوائيات ذات النطاق الواسع جداً، هوائيات النطاق المزدوج.

Abstract

Biomedical antennas play a vital role in modern healthcare technologies, supporting implantable devices, wearable sensors, and telemedicine through reliable wireless communication. These antennas require compact size, high efficiency, and strict specific absorption rate compliance for safe operation. This thesis introduces an inverse artificial neural network approach combined with multi-objective optimization to enhance the design process of biomedical antennas. The proposed method enables direct prediction of antenna geometries from target performance metrics, reducing computational time while maintaining high accuracy. Case studies on ultra-wideband and dual-band antennas demonstrate the effectiveness of the proposed models in achieving miniaturization, impedance matching, and specific absorption rate optimization.

Keywords: Biomedical antenna, specific absorption rate, miniaturization, inverse artificial neural networks, multi-objective optimization, ultra-wideband antennas, dual-band antennas.

Résumé

Les antennes biomédicales jouent un rôle essentiel dans les technologies modernes de soins de santé, en permettant une communication sans fil fiable pour les dispositifs implantables, les capteurs portables et les systèmes de télémédecine. Ces antennes doivent présenter une taille compacte, une efficacité élevée et une conformité stricte au taux d'absorption spécifique afin d'assurer un fonctionnement sûr à l'intérieur du corps humain. Ce travail propose une méthodologie avancée basée sur les réseaux de neurones artificiels inverses combinée à l'optimisation multi-objectif pour améliorer le processus de conception des antennes biomédicales. L'approche développée permet de prédire directement les dimensions géométriques de l'antenne à partir des performances électromagnétiques souhaitées, réduisant considérablement le temps de simulation tout en maintenant une grande précision. Cette méthodologie est appliquée à des études de cas incluant la conception et l'optimisation d'antennes à très large bande et d'antennes à double bande destinées aux applications industrielles, scientifiques et médicales. Les résultats obtenus démontrent l'efficacité du modèle proposé pour la miniaturisation, l'adaptation d'impédance et la réduction du taux d'absorption spécifique.

Mots clés : antenne biomédicale, taux d'absorption spécifique, miniaturisation, réseaux de neurones artificiels inverses, optimisation multi-objectif, antennes à très large bande, antennes à double bande.

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List of Abbreviations

AI:	Artificial Intelligence
ANN:	Artificial Neural Network
CST:	Computer Simulation Technology (Microwave Studio)
CNN:	Convolutional Neural Network
DL:	Deep Learning
ECG:	Electrocardiogram
EM:	Electromagnetic
FCC:	Federal Communications Commission
FBW:	Fractional Bandwidth
FDTD:	Finite Difference Time Domain
FEM:	Finite Element Method
FFBPN:	Feed-Forward Backpropagation Network
GA:	Genetic Algorithm
GAN:	Generative Adversarial Network
GPR:	Gaussian Process Regression
GRNN:	General Regression Neural Network
HFSS:	High-Frequency Structure Simulator
ICNIRP:	International Commission on Non-Ionizing Radiation Protection
IMD:	Implantable Medical Device

IoT:	Internet of Things
ISM:	Industrial, Scientific and Medical (band)
LSTM:	Long Short-Term Memory
ML:	Machine Learning
MLP:	Multi-Layer Perceptron
MICS:	Medical Implant Communication Service
MoM:	Method of Moments
MSE:	Mean Squared Error
PNA-L:	Agilent Vector Network Analyzer
PSO:	Particle Swarm Optimization
RNN:	Recurrent Neural Network
RZF:	Reconfigurable Z-shaped Fractal
SAR:	Specific Absorption Rate
S11:	Reflection Coefficient (Scattering Parameter)
SLP:	Single-Layer Perceptron
SVM:	Support Vector Machine
UWB:	Ultra-Wideband
VNA:	Vector Network Analyzer
VSWR:	Voltage Standing Wave Ratio
WBAN:	Wireless Body Area Network
WPT:	Wireless Power Transfer

General introduction

Wireless communication technologies have become indispensable in modern healthcare care, supporting applications such as remote patient monitoring, telemedicine, and telehealth services. At the core of these systems are antennas, which enable reliable data transmission both within the human body and between biomedical devices and external platforms [1].

However, designing antennas for biomedical applications presents unique challenges. Such antennas must be compact, biocompatible, energy efficient and comply with strict limits of electromagnetic exposure [2]. Traditional electromagnetic (EM) simulations, while accurate, are computationally demanding and time-consuming, particularly when multiple design variations must be evaluated [3–5]. These limitations slow the design cycle and restrict real-time optimization, both of which are increasingly critical in fast-paced healthcare environments.

To overcome these constraints, researchers have turned to advanced optimization methods, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO) [6, 7], and Artificial Neural Networks (ANNs) [8, 9]. Among these, ANNs have emerged as especially powerful tools because of their ability to learn complex nonlinear relationships, predict antenna performance from limited data, and accelerate the optimization process.

This thesis investigates the integration of ANNs in the design and optimization of miniature biomedical antennas. The work addresses fundamental design principles, explores the role of machine learning in antenna optimization, and applies ANN-based models to practical case studies involving implantable, wearable, and dual-band biomedical antennas. The

study further introduces multi-objective inverse ANN models to identify optimal antenna geometries directly from desired performance metrics.

Through these contributions, the thesis aims to enhance the efficiency, adaptability, and reliability of biomedical antenna design, paving the way for innovative healthcare technologies that combine advanced wireless communication with intelligent optimization techniques.

Problem and Motivation

Traditional electromagnetic (EM) simulations are essential for antenna design, but they suffer from several limitations. They require detailed meshing and complex modeling of electromagnetic interactions with biological tissues, making the process computationally intensive and time-consuming. These challenges are amplified when designing miniature, broadband, or multifunctional biomedical antennas, where repeated simulations are necessary to evaluate different geometrical variations.

Conventional optimization methods, such as gradient-based algorithms or evolutionary approaches, often struggle with highly nonlinear and multidimensional design spaces. They may converge slowly or become trapped in local optima, leading to suboptimal results. As a consequence, the overall design process becomes iterative and inefficient, delaying the development of reliable biomedical antennas.

To address these issues, researchers have increasingly turned to Machine Learning (ML) techniques. In particular, Artificial Neural Networks (ANNs) offer the ability to learn complex input–output relationships directly from data. Once trained, ANN models can rapidly predict antenna performance without the need for full-scale EM simulations, significantly reducing computational cost. This capability motivates the present research, which investigates how ANNs can be effectively integrated into the design and optimization of biomedical antennas.

Objectives

The primary objective of this thesis is to develop efficient and accurate methods for the design and optimization of miniature biomedical antennas using Artificial Neural Networks.

The specific goals are:

1. To analyze the fundamental requirements of biomedical antennas, including miniaturization, SAR compliance, biocompatibility, and efficient wireless communication.
2. To investigate the potential of Machine Learning techniques, particularly ANNs, in predicting antenna performance and accelerating the design process.
3. To apply ANN-based models to practical case studies, including implantable, wearable, and dual-band biomedical antennas, and validate results through comparison with EM simulations and experimental measurements.
4. To propose multi-objective inverse ANN models capable of mapping desired performance specifications directly to optimal antenna geometries.
5. To demonstrate the advantages of ANN-assisted optimization in reducing computational cost, improving design accuracy, and enabling more adaptable antenna structures for biomedical applications.

Thesis Contribution

This thesis makes several key contributions to the field of biomedical antenna design and optimization:

1. Development of ANN-based optimization methodologies that significantly reduce computational time compared to conventional EM simulations while maintaining high accuracy.

2. Comprehensive review of biomedical antenna requirements with emphasis on miniaturization techniques, impedance matching, and SAR compliance.
3. Implementation of case studies, including circular slotted patch antennas, UWB antennas, and dual-band ISM antennas optimized using ANN-PSO models.
4. Proposal and validation of inverse ANN models for multi-objective optimization, enabling the direct prediction of antenna geometries from target performance metrics.
5. Experimental verification through antenna fabrication and measurement, confirming the practical feasibility of the proposed approaches.

Thesis Organization

The structure of this dissertation is organized into four main chapters, in addition to the general introduction and conclusion:

- **Chapter 1: Fundamentals of Biomedical Antenna Design.**

This chapter presents the fundamental principles of antenna theory applied to biomedical systems. It classifies biomedical applications into in-body, on-body, and off-body devices, and highlights key requirements such as miniaturization, SAR compliance, biocompatibility, and efficient communication. Different design techniques, including planar antennas, metamaterials, fractals, and advanced simulation tools, are also reviewed.

- **Chapter 2: Machine Learning Methods for Antenna Design.**

This chapter provides a comprehensive overview of Machine Learning (ML) and its relation to Artificial Intelligence (AI) and Deep Learning (DL). It introduces supervised, unsupervised, and reinforcement learning, with emphasis on methods such as SVM,

GPR, and ANN. Special focus is given to neural networks, their architectures, learning principles, and their role in antenna optimization.

- **Chapter 3: Artificial Neural Networks for Antenna Optimization.**

This chapter discusses the use of Artificial Neural Networks (ANNs) in the optimization of biomedical antennas. It analyzes ANN learning algorithms, training strategies, and performance. Several case studies are presented, including circular slotted patch antennas, UWB antennas, and a dual-band ISM antenna optimized with ANN and PSO. Results are validated through simulation and experimental measurements.

- **Chapter 4: Inverse Neural Networks for Multi-Objective Biomedical Antenna Design.**

This chapter introduces inverse ANN models developed for multi-objective optimization. Different ANN models are compared, and the proposed model is applied to design antennas directly from target performance specifications. Applications are studied in free space and within tissue environments, with detailed validation through numerical simulations and prototype fabrication.

- **General Conclusion.**

The dissertation concludes by summarizing the main contributions, highlighting the advantages of ANN-assisted optimization in biomedical antenna design, and suggesting perspectives for future research.

Chapter 1

Fundamentals of Biomedical Antenna Design

1.1 Introduction

Biomedical applications are increasingly relying on advanced antenna technologies to support communication, sensing, and therapeutic functions. Antennas play a crucial role in enabling reliable wireless links between implantable devices, wearable sensors, and external monitoring systems. However, designing antennas for biomedical use involves unique requirements such as compact size, biocompatibility, safe operation within the human body, and compliance with electromagnetic exposure limits.

This chapter introduces the fundamental principles of biomedical antenna design and highlights the specific challenges associated with in-body, on-body, and off-body applications. Special attention is given to design parameters such as miniaturization, impedance matching, bandwidth, radiation efficiency, and Specific Absorption Rate (SAR). In addition, modern design approaches are reviewed, including the use of metamaterials, fractal geometries, and advanced simulation tools, to demonstrate how antennas can be optimized for safe and efficient operation in medical settings.

By establishing this foundation, the chapter provides a comprehensive context for ex-

ploring optimization strategies, including the integration of Artificial Intelligence (AI) and Machine Learning (ML) methods, which will be the focus of the following chapters.

1.2 Overview of Biomedical Applications that Require Antenna Technology

Antenna technology is essential in the development and operation of biomedical devices. These devices can be classified on the basis of their position relative to the human body: inside the body (In-Body), worn on the body (On-Body), or interacting from outside the body (Off-Body). Each category imposes specific requirements and challenges for antenna design. The following classification presents the main biomedical applications that require antenna integration:

1.2.1 In-Body Applications

These applications involve devices that are implanted and operate within the human body. They require compact, biocompatible antennas capable of efficient communication through lossy biological tissues, where signal attenuation is significant due to high permittivity and conductivity.

1.2.1.1 Implantable Medical Devices (IMDs)

Pacemakers and Defibrillators Antennas are used for wireless communication to monitor heart conditions, adjust settings, and transmit patient data . These antennas must be designed to operate efficiently within the thoracic cavity and ensure minimal power loss. In Figure 1.1, advanced wireless power transfer (WPT) techniques, enhanced by metasurfaces, are used to efficiently power these pacemakers, highlighting the sophistication of modern IMD systems [1].

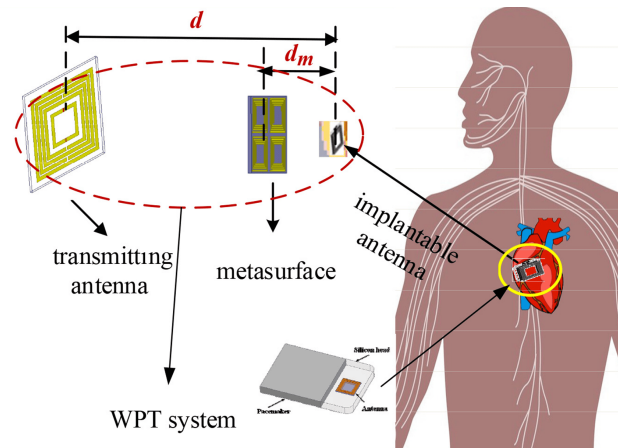


Figure 1.1: Advanced Wireless Power Transfer Techniques for Pacemaker Applications

Neural Implants Devices such as deep brain stimulators use antennas to communicate with external controllers to treat neurological disorders such as Parkinson's disease . Figure 1.2 demonstrates the antenna design for neural implants, emphasizing how the broadside radiation pattern of the implantable antenna facilitates the efficient transmission of brain signals to external receivers [10].

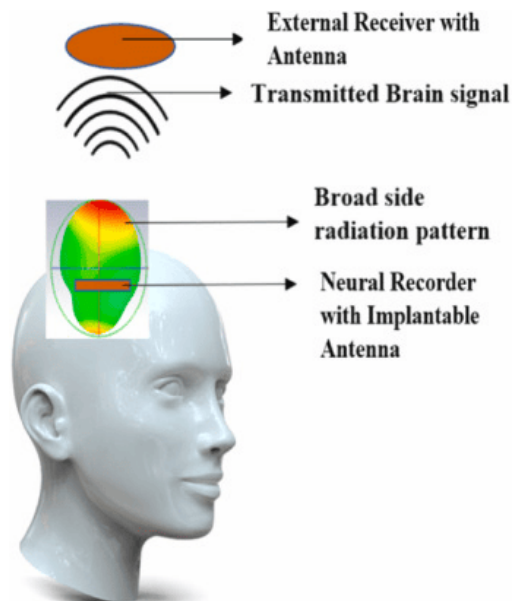


Figure 1.2: Antenna Design for Neural Implants: Enhancing Brain Signal Transmission with Implantable and External Receivers

Smart Drug Delivery Systems Smart drug delivery systems use antennas to receive signals from external controllers, ensuring accurate and timely drug delivery. Figure 1.3 shows a capsule-based targeted drug delivery system. Under the impact of external actuation, the medication is released from the device via tiny microneedles [11].

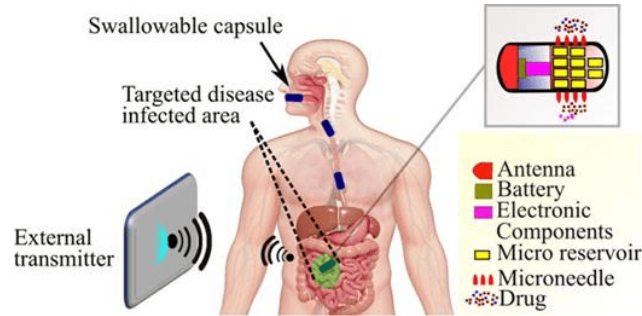


Figure 1.3: Smart drug delivery systems use antennas

Ingestible Devices These include capsule endoscopy systems that transmit physiological data (pH, temperature, pressure) while traveling through the gastrointestinal tract. The antenna in such devices must provide omnidirectional radiation and stable impedance matching as the device moves and rotates within the body.

1.2.2 On-Body Applications

These refer to devices placed on or in direct contact with the skin, designed to continuously monitor vital signs. Antennas must maintain efficiency despite proximity to the body and motion-induced detuning. Flexibility, comfort, and minimal electromagnetic exposure to the user are additional considerations.

1.2.2.1 Wearable Health Monitors

Fitness Trackers and Smartwatches These devices use antennas to transmit vital signs and activity data to smartphones or healthcare systems, allowing continuous health monitoring [12]. Figure 1.4 illustrates the diverse applications of wireless monitoring technologies in

biomedical settings, showcasing how temperature, heart rate, and glucose levels are tracked using various wearable devices .

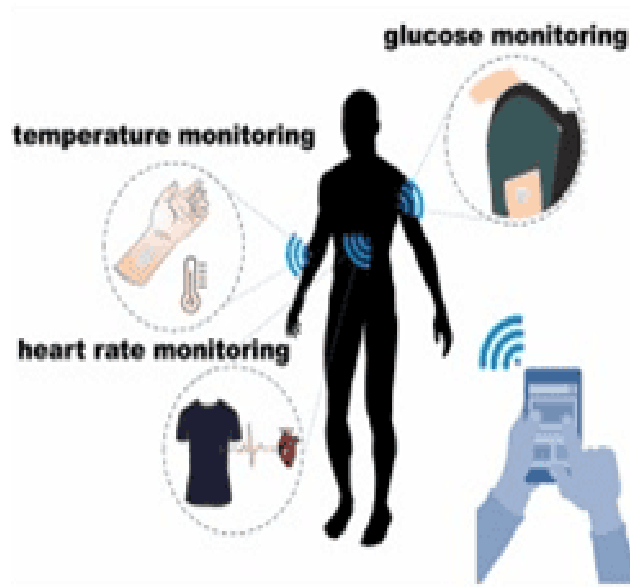


Figure 1.4: Wireless Monitoring Technologies for Biomedical Applications

Wearable ECG Monitors Wearable ECG monitors with embedded antennas can transmit real-time heart data to healthcare providers, helping to detect early cardiac conditions. Figure 1.5 shows a system in which ECG signals are captured using an RZF antenna, uploaded to the cloud, and remotely monitored via IoT for real-time health tracking [13].

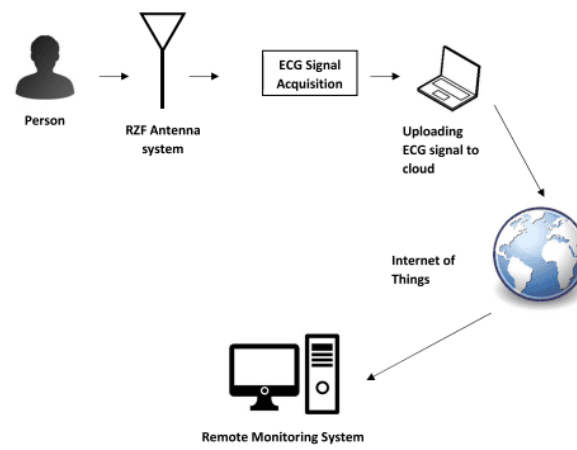


Figure 1.5: IoT-Based Remote ECG Monitoring with RZF Antenna

Glucose Monitoring Systems Continuous glucose monitoring devices utilize antennas to send blood sugar levels to external displays, helping diabetic patients manage their condition effectively. Figure 1.6 illustrates a wireless insulin delivery system. In part (a), a needle-type sensor connected to an external RF unit monitors glucose levels and transmits data through an antenna to an insulin pump. In part (b), a cross-sectional view shows the placement of the antenna beneath the skin, transmitting data to two receivers: one for the insulin pump and another for a personal computer, facilitating continuous monitoring and precise insulin administration. The system operates within the MICS and ISM bands for reliable data communication [14].

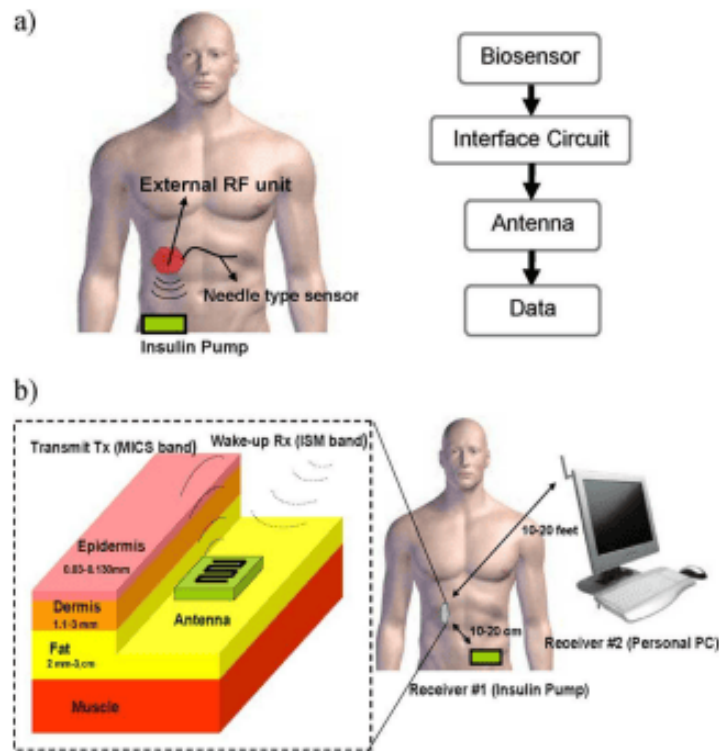


Figure 1.6: Wireless Insulin Delivery System Using RF Communication

Wireless Body Area Networks (WBANs) Wireless Body Area Networks (WBANs) consist of multiple sensors and actuators placed inside or outside the body, wirelessly con-

nected through antennas, as shown in Figure 1.7 [15]. These networks are used for comprehensive health monitoring, telemedicine, and remote patient management, allowing real-time data exchange and continuous patient care [16].

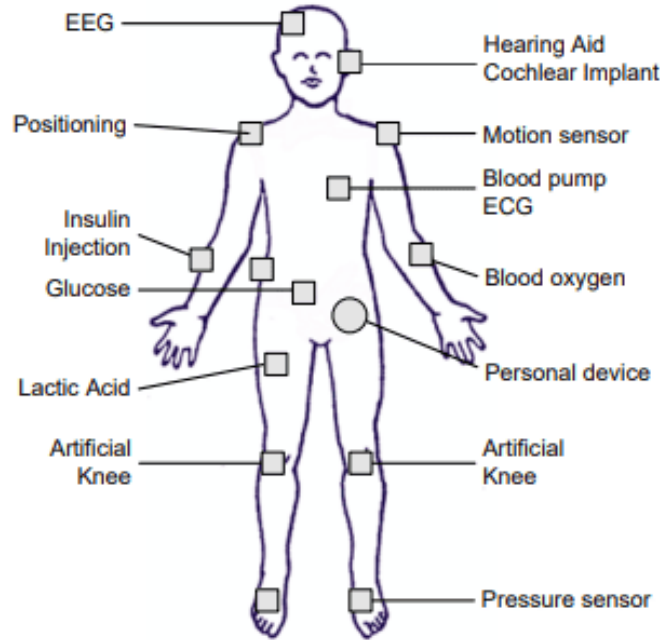


Figure 1.7: Wireless Body Area Network for Comprehensive Health Monitoring

1.2.3 Off-Body Applications

Off-body applications involve antennas that facilitate communication between body-mounted or implanted devices and remote infrastructure or diagnostics systems. These require antennas with sufficient range and robustness against environmental interference.

Telemedicine and Remote Monitoring Antennas are essential in telemedicine systems, allowing the transmission of patient data from remote locations to healthcare providers. This technology is particularly beneficial for patients in rural or underserved areas [17]. Figure 1.8 illustrates the integration of various health monitoring platforms in telemedicine systems, highlighting the role of antennas in facilitating real-time data transmission between patients

and healthcare providers.



Figure 1.8: Health Monitoring Platforms in Telemedicine

Microwave Imaging Antennas are used in imaging modalities such as magnetic resonance imaging (MRI) and microwave imaging for noninvasive diagnostics. They enable high-resolution imaging of tissues and organs, aiding in the early detection and treatment of diseases [18].

Figure 1.9 demonstrates the use of antennas in microwave imaging, where S parameters are measured and utilized for image reconstruction, helping to identify dielectric contrasts within tissues [19].

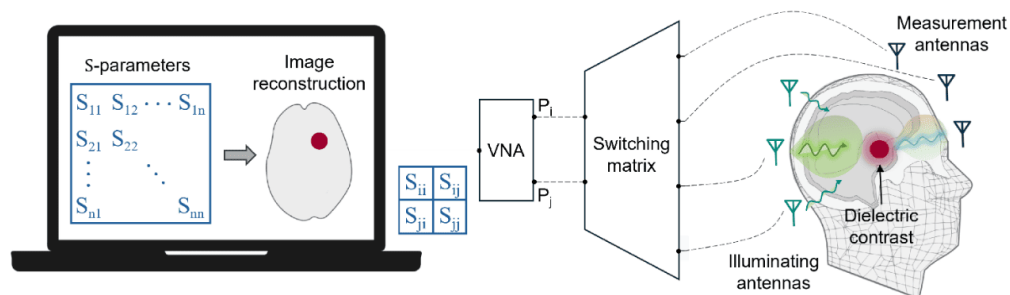


Figure 1.9: Antenna-Based Microwave Imaging System for Non-Invasive Diagnostics

1.3 Importance of Antenna Design in Biomedical Devices

Antenna design is a critical aspect of biomedical devices due to its direct impact on the performance, safety, and efficacy of wireless communication systems within the body. As biomedical devices increasingly rely on wireless technology for monitoring, diagnosis, and treatment, the role of antennas becomes pivotal in ensuring effective and reliable communication. The following are some key points that highlight the importance of antenna design in biomedical devices.

1.3.1 Efficient Wireless Communication

Biomedical devices, such as implantable sensors, wearable monitors, and wireless medical instruments, depend on antennas to transmit and receive signals. The efficiency of these antennas directly influences the quality of data transmission [20, 21], ensuring that critical health information is accurately communicated between the device and external systems.

1.3.2 Miniaturization and Integration in Biomedical Antennas

Miniaturization is a critical requirement in the design of biomedical antennas, especially for implantable and wearable devices. These devices often require compact and lightweight designs due to space constraints and the need for patient comfort. Therefore, antenna design must prioritize miniaturization while maintaining performance, allowing seamless integration into small devices without compromising functionality [22, 23].

The need for miniaturized antennas arises from the need to integrate them into complex medical devices. Such antennas must not only be small, but also meet stringent performance criteria:

- **Space Constraints:** Biomedical devices have limited available space for antenna in-

tegration, requiring highly compact designs.

- **Performance Requirements:** Miniaturized antennas must maintain adequate performance in terms of gain, efficiency, and bandwidth to ensure reliable communication and functionality.
- **Biocompatibility and Safety:** The materials and designs used must be safe for use within or in the human body, with minimal impact on surrounding tissues.

To achieve necessary size reductions while maintaining or enhancing antenna performance, several techniques are employed:

1.3.2.1 Planar Antennas

Planar antennas are widely used in biomedical applications because of their compact form factor and ease of integration with other circuit components:

- **Microstrip Patch Antennas:** These antennas are popular for their low profile and ease of fabrication [24, 25]. They consist of a radiating patch on a dielectric substrate with a ground plane. Achieving miniaturization often requires the use of high-permittivity substrates or innovative patch shapes.
- **Coplanar Waveguide Antennas:** CPW antennas offer advantages in miniaturization with a single metal layer featuring ground conductors on the same plane as the signal conductor, simplifying fabrication and allowing compact designs, especially in flexible applications [26, 27].

1.3.2.2 Metamaterials and Metasurfaces

Metamaterials and metasurfaces enable novel approaches to antenna miniaturization:

- **Metamaterials:** Designed to exhibit negative permittivity or permeability, metamaterials allow antennas to be significantly smaller than conventional designs, manipulating electromagnetic waves to achieve compact and efficient antennas [28, 29].
- **Metasurfaces:** These two-dimensional materials can create ultrathin antennas with enhanced control over wave propagation, reducing size while maintaining desirable radiation characteristics [30, 31].

1.3.2.3 Fractal Antennas

Fractal antennas utilize self-similar geometries to create compact designs with wide bandwidth:

- **Utilizing Fractal Geometry:** Geometries such as the Sierpinski triangle maximize the effective length of the antenna within a confined space, allowing operation at multiple frequencies or in broad bandwidths [32, 33].
- **Space-Efficient Designs:** The recursive nature of fractal geometries reduces physical size while achieving the necessary electrical length, making them ideal for space-constrained applications [34, 35].

1.3.2.4 Material Selection and Advanced Manufacturing

The choice of material and manufacturing techniques are crucial for miniaturizing biomedical antennas.

- **Advanced Materials:** Flexible substrates and biocompatible coatings are essential for creating safe and effective antennas for use in or on the human body [36].
- **3D Printing and Additive Manufacturing:** These techniques allow the creation of complex miniaturized antenna structures with precise control over the geometry and properties of the material, facilitating the development of custom designs [37].

1.3.3 Specific Absorption Rate (SAR) Compliance

SAR measures the rate at which the body absorbs electromagnetic energy from a device. For example, a pacemaker operating at 1 mW (0.001 W) with an absorption mass of 10 grams would have an SAR of 0.1 W/kg, which is well within safety standards. In biomedical applications, antennas must be designed to minimize SAR to ensure patient safety, particularly for implantable devices. Low SAR values reduce the risk of tissue heating and potential damage, making it a crucial consideration in antenna design [38].

The Specific Absorption Rate (SAR) is calculated using the following equation.

$$\text{SAR} = \frac{\sigma E^2}{\rho} \quad (1.1)$$

Where:

- σ is the electrical conductivity of the tissue (measured in S/m),
- E is the root-mean-square (RMS) value of the electric field (measured in V/m),
- ρ is the mass density of the tissue (measured in kg/m³).

This equation quantifies the SAR in watts per kilogram (W/kg), reflecting the energy absorbed by body tissues [39]. For safety compliance, the Federal Communications Commission (FCC) has set SAR limits to regulate electromagnetic exposure. For devices operating close to the body, the FCC specifies an SAR limit of 1.6 W/kg averaged over 1 gram of tissue, while the International Commission for Nonionizing Radiation Protection (ICNIRP) recommends a limit of 2.0 W/kg averaged over 10 grams of tissue. In biomedical applications, particularly for implantable devices, it is essential to maintain SAR below these regulatory thresholds to prevent tissue heating, which could lead to cell damage or discomfort.

1.3.4 Techniques for Reducing Specific Absorption Rate (SAR)

SAR is a critical safety metric, especially in medical devices where the antennas are near or inside the human body. This section discusses various strategies for reducing SAR:

- **Antenna Placement:** Positioning the antenna at a safer distance from vital tissues minimizes exposure to electromagnetic radiation. By carefully placing the antenna further from critical areas, the intensity of radiation absorbed by sensitive tissues can be significantly reduced, which is especially important in implanted or wearable medical devices [40, 41].
- **Material Selection:** Choosing materials with lower conductivity or permittivity can help control the distribution of electromagnetic waves. Materials with low conductivity limit the induced currents within tissues, while low-permittivity materials reduce wave penetration, confining electromagnetic energy within the antenna structure rather than allowing it to reach surrounding tissues [42, 43].
- **Shielding Techniques:** Using multilayer structures or metamaterials can absorb or reflect radiation away from the body. Metamaterials, engineered to exhibit specific electromagnetic properties, can direct or deflect electromagnetic waves, while multilayer designs using conductive and nonconductive layers create barriers that minimize radiation exposure. In addition, radiation-absorbing coatings can be applied to the antenna structure to absorb specific frequencies, thereby reducing radiation levels that penetrate body tissues [43].
- **Power Input:** The power input of an antenna directly influences the SAR value. Reducing input power can effectively reduce electromagnetic energy absorbed by surrounding tissues, improving patient safety. Reducing the power supplied to the antenna reduces the amount of electromagnetic energy absorbed by the body [44–46]. Reducing

the power input lowers the electric field E , which in turn reduces the SAR. This is particularly important when the antenna operates in close proximity to human tissues. To determine the power input required to achieve a specific Specific Absorption Rate (SAR) value, we can use the formula:

$$\text{SAR} = \frac{P}{m}. \quad (1.2)$$

Where P represents the power absorbed by the tissue, measured in watts (W), and m denotes the mass of the tissue, measured in kilograms (kg).

1.3.5 Operational Frequency and Bandwidth

The selection of appropriate operational frequency bands (such as ISM, MICS, or UWB) is essential for ensuring reliable communication in biomedical applications. Bandwidth refers to the range of frequencies over which the antenna can operate effectively. Biomedical antennas often need to accommodate a wide bandwidth to support various communication protocols and data rates.

In particular, devices that monitor multiple physiological parameters may require a wide bandwidth to transmit data simultaneously. In addition, antennas must provide sufficient bandwidth to accommodate the data transmission requirements of medical devices.

The Federal Communications Commission (FCC) defines Ultra-Wideband (UWB) technology as a spectrum that occupies a bandwidth of at least 500 MHz or 20% of the center frequency [47, 48]. UWB antennas are crucial for a wide range of applications, including wireless communications and biomedical systems, due to their ability to support high data rates and provide precise localization.

According to the FCC, the fractional bandwidth (FBW) of a UWB signal is given by:

$$FBW = \frac{f_H - f_L}{f_C} \quad (1.3)$$

where f_H and f_L are the highest and lowest frequencies in the UWB band, and f_C is the center frequency.

1.3.5.1 Frequency

The operating frequency of the antenna must align with the specific application. Biomedical applications often require antennas to operate at frequencies that can penetrate human tissue effectively, such as Industrial, Scientific, and Medical (ISM) bands. As shown in Table 1.1, various frequency bands have been extensively studied in the literature for their applications in biotelemetry. These frequency ranges, such as the 401–406 MHz MedRadio band and ISM bands, offer various advantages according to the application, with higher frequencies generally allowing smaller antennas and higher communication speeds, while lower frequencies exhibit better penetration through biological tissues due to lower losses.

Table 1.1: Antennas for bio-telemetry presented in the literature classified by working frequency.

Frequency Band	References
401 – 406 MHz	[49–59]
433 MHz	[50, 58, 60–63]
860 – 960 MHz	[50, 64–69]
1.2 – 1.5 GHz	[14, 57, 58, 66, 70–74]
2.4 – 2.5 GHz	[63, 69, 70, 75–78]
5.8 GHz	[79–82]

1.3.6 Directional Control and Gain

In some biomedical applications, such as targeted drug delivery systems or remote monitoring, high-gain directional antennas are essential to focus energy toward specific areas of the body.

Proper antenna design ensures that signals are directed precisely, improving the effectiveness of the device and reducing power consumption. [83, 84]

1.3.7 Advanced Simulation Tools for Antenna Design

Methods for synthesizing and analyzing antennas involve a broad spectrum of techniques used to design, model, and evaluate antenna systems effectively. Initially, numerical techniques such as the Method of Moments (MoM) [85], Finite Element Method (FEM) [86], and Finite Difference methods [87] were widely adopted, but often present challenges due to their programming complexity and computational demands. To overcome these obstacles, specialized software tools such as CST Microwave Studio, HFSS (High-Frequency Structure Simulator) and FEKO have been developed, allowing engineers to implement these techniques more effectively. However, designing and optimizing electromagnetic (EM) structures with these tools can be highly CPU intensive, requiring significant computational resources to identify optimal design parameters [3–5]. To address these time and resource constraints, researchers have increasingly adopted advanced optimization techniques that reduce computational time, including genetic algorithms (GA), particle swarm optimization (PSO) [6], and artificial neural networks (ANN). These methods streamline the design process and enhance efficiency, making them invaluable for modern antenna development.

1.3.7.1 AI in Practice

The practical applications of AI in antenna design demonstrate its transformative potential:

- **Dynamic Parameter Adjustment:** AI-driven systems can monitor antenna performance in real time and dynamically adjust parameters to maintain optimal operation under varying conditions. This capability is crucial for biomedical applications where environmental factors can affect performance, ensuring consistent functionality.

- **Rapid Iteration:** AI enables the rapid exploration of thousands of design configurations in minutes. This accelerates the design process, allowing engineers to evaluate more options and quickly identify the most promising designs. As a result, AI reduces the time to market for new biomedical antennas, facilitating timely advancements in medical technology.
- **Enhanced Design Efficiency:** By integrating AI into the design workflow, engineers can achieve higher efficiency and innovation. The ability to quickly simulate and evaluate diverse design options fosters creativity and leads to the development of antennas that are more tailored to specific biomedical applications.

1.4 Conclusion

In this chapter, we examined the essential aspects of biomedical antenna design, from fundamental principles to practical applications. The discussion covered in-body, on-body, and off-body devices, emphasizing the challenges of ensuring reliable communication while maintaining patient safety and comfort. Miniaturization techniques, SAR compliance strategies, and advanced simulation tools were reviewed as key enablers for effective antenna performance.

The analysis shows that while conventional methods provide solid design frameworks, they are often limited by computational cost and design complexity. This highlights the need for more efficient approaches, such as AI-driven optimization, to accelerate the design process and improve performance. Building on this background, the next chapter will introduce Machine Learning techniques and investigate how they can be applied to enhance antenna design and optimization.

Chapter 2

Machine Learning Methods for Antenna Design

2.1 Introduction

Building upon the principles of biomedical antenna design presented in the previous chapter, this chapter introduces Machine Learning (ML) as a powerful tool for antenna optimization. Machine Learning, which lies at the intersection of artificial intelligence (AI), statistics, and optimization theory, provides data-driven methods to model complex systems and accelerate design processes.

The chapter begins with a brief overview of the historical development of ML and clarifies its relationship with Artificial Intelligence (AI) and Deep Learning (DL). It then presents the main categories of ML—supervised, unsupervised, and reinforcement learning—followed by a discussion of widely used algorithms such as Support Vector Machines (SVM), Gaussian Process Regression (GPR), and Artificial Neural Networks (ANN). Special emphasis is placed on ANN due to its flexibility and high accuracy in handling nonlinear problems, particularly in electromagnetic and antenna design tasks.

By highlighting the role of ML in enhancing antenna design, this chapter establishes the theoretical background necessary to understand the detailed exploration of Artificial Neural

Networks in Chapter 3.

2.2 Machine Learning

ML is a multidisciplinary subject that includes statistics, optimization theory, probability theory, and more. His fundamental idea is to use previous data and experiences to learn from, then automatically improve the algorithm performance to get ideal results [88, 89]. The nature and characteristics of data Algorithms, experience, and performance are the essential elements of ML [90, 91] . Three active periods can be easily distinguished in the history of machine learning.

2.3 History Machine Learning

1950s - 1960s : Early research conducted in the 1950s and 1960s was motivated by findings in the fields of neurophysiology, biology, and psychology. Several research teams created and evaluated computer models of neurons, the most notable of which being Rosenblatt's (1958) perceptron. In an attempt to understand how random mutation and natural selection lead to intelligent algorithms, other groups experimented with simulated evolution (Friedberg, 1958; Friedberg, Dunham, & North, 1959; Fogel, Owens,&Walsh,1966). Further studies (Hunt, Marin, & Stone, 1966; Evans, 1968) constructed basic symbol processing systems to simulate human learning in psychological laboratory settings. (Feinbaum, 1961). Apart from the preliminary investigation of supervised learning approaches, Samuel (1959, 1967) conducted a thorough study on the challenge of accelerating learning [92] Then between the 1970s and 1980s: The era was marked by the creation of more useful algorithms, the significant amount of information and data gathered by the ML system, and constant advancements in learning techniques and tactics. (Royce, 1970)Significant research on the "knowledge acquisition bottleneck" in the block world area, META-DENDRAL learned mass spectrometry prediction

rules. [93] 1980s: experimentation with various methods and a greater focus on assessment; Mitchell (1982) established the idea of "version spaces," while Quinlan (1983) developed the idea of "inductive bias" in collaboration with Utgoff. developed the decision tree algorithm known as ID3. The concept of "probably approximately correct" (PAC) learning was introduced by Valiant in 1984 and remains the most often used theoretical framework. Numerous shortcomings of the perceptron were overcome by the backpropagation technique (Rumelhart, 1986). Decision tree and rule learning continued to advance, while explanation-based, speed-up, and case-based learning gained popularity. An example of explanation-based learning and speeding up learning includes the utility problem, analogy, reconnectionism (PDP, ANN). Everyone agrees that deep learning is a subset of Machine Learning and that Machine Learning is a subset of artificial intelligence [94], as shown in Figure 2.1.

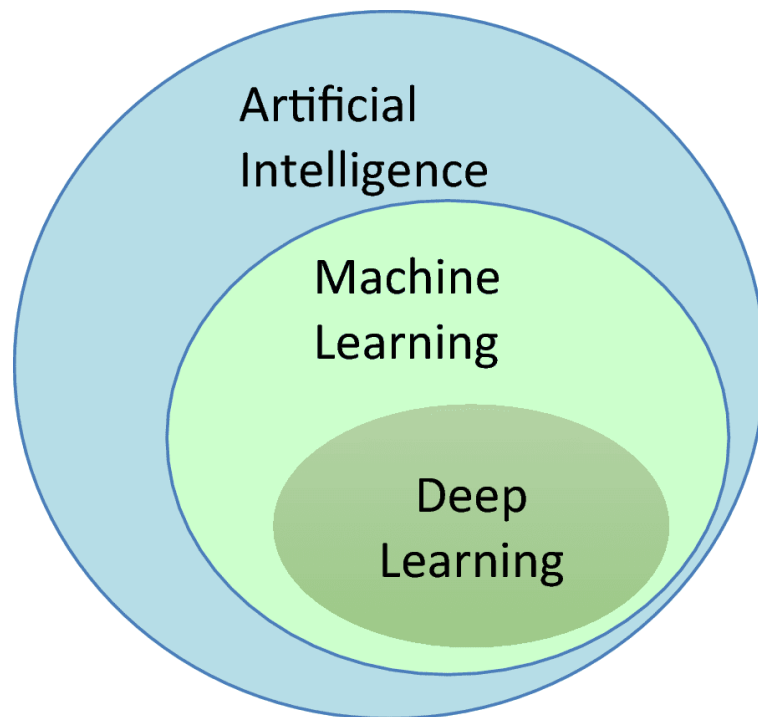


Figure 2.1: The connection between deep learning, Machine Learning, and artificial intelligence

2.4 deep learning vs Machine Learning vs artificial intelligence

AI is the general discipline of building intelligent systems; ML is a subset of AI that focuses on data-driven learning; and DL is a subset of ML that leverages deep neural networks to discover intricate patterns. Even though DL is an effective technique in Machine Learning, Machine Learning is only one strategy in the larger subject of artificial intelligence as shown in Figure 2.1.

2.5 The Categories of Machine Learning

ML can be broadly categorized into three main areas:

Figure 2.2 illustrates reinforcement learning [95], unsupervised learning [96], and supervised learning [97]. In supervised learning, may be defined as the process of fine-tuning model

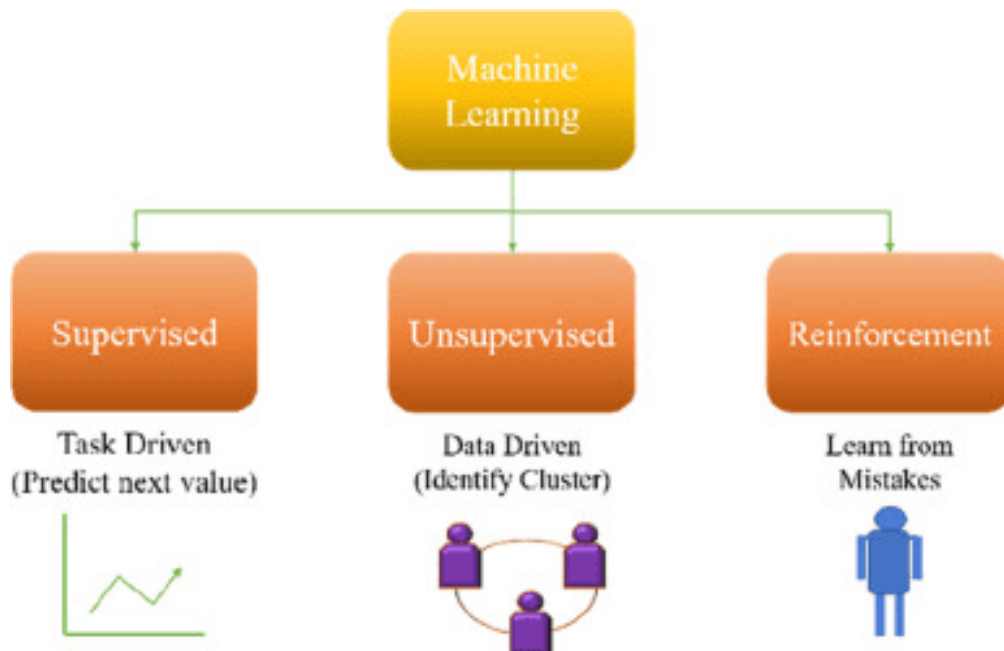


Figure 2.2: Categories of Machine Learning

parameters using labeled data sets in order to make the model function for bigger and un-

seen data. Testing the chosen model on a different set of data allows for an evaluation of its performance [98]. In unsupervised learning, this method, as opposed to supervised learning, trains the learning algorithm using an input data set without any labeled outputs. No output is right or incorrect for any given input item, and unlike supervised learning, no human intervention is required for correction or adaptation [99]. In reinforcement learning, model feedback is derived from the input data. In comparison with supervised learning, the input data is solely utilized as a criterion to verify if the model has been corrected, And in another way we do not assume that targets for the agent's desired behavior exist; we do assume that there is some observable metric that tells the agent how well it is performing [100].

2.6 Applications of Machine Learning

In biodiesel research, Machine Learning (ML) technology is applied to improve production efficiency, economic feasibility, and environmental sustainability through real-time monitoring and control of systems [101]. According to research, Machine Learning technology is extensively utilized in network analysis, banking, marketing, and telecommunications [102]. in [103] processed the declining accuracy of existing approaches due to the diversity of Internet application traffic by evaluating application-level traffic categorization using supervised Machine Learning algorithms. In order to address basic restrictions of learning algorithms and highlight future research directions to overcome the physical constraints of sensors, in [104] machine learning approaches utilized in wireless sensor networks (WSNs) have been covered to tackle networking and application difficulties. Many works in the subject of electrical and computer engineering have been published in the literature. ML has contributed to improvement, These works include sensor networks ,we mention: also deep learning-based detection and decoding [105–108]. Antenna engineering uses Machine Learning and deep learning techniques to improve design and optimization approaches [109].

2.7 Machine Learning methods

2.7.1 Support Vector Machine (SVM)

SVM is a popular Supervised Learning algorithm that divides the n-dimensional space into classes by determining the optimal line or choice limit, known as a hyperplane, for classification in Machine Learning [110]. All it takes to comprehend the fundamentals of SVM classification are four understandings: the soft margin, the maximum-margin hyperplane, the separating hyperplane, and the kernel function, as illustrated in Figure 2.3.

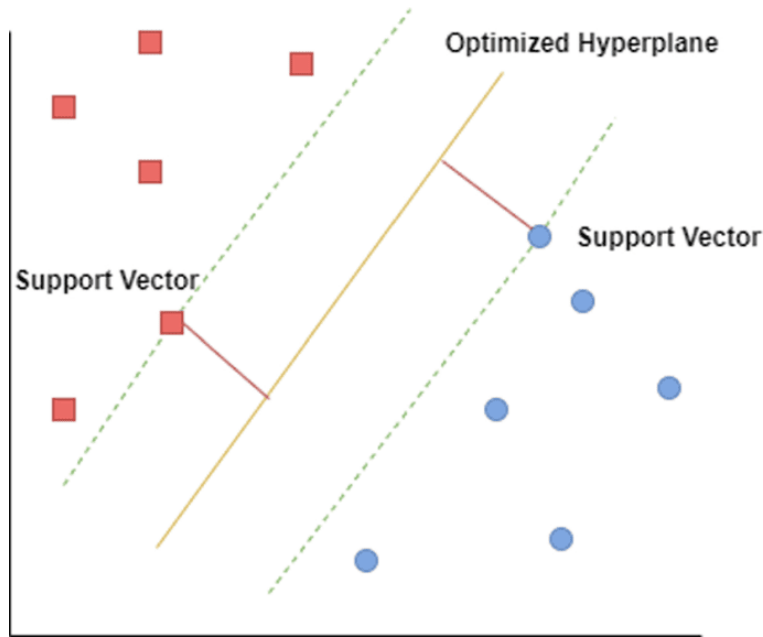


Figure 2.3: A support vector machine's (SVM) schematic diagram

The function $f(x)$ for linear classification is shown as [111]:

$$f(x) = \mathbf{w}^T \mathbf{x} + b \quad (2.1)$$

where b is a deviation and $\mathbf{w}^T$ is a weight vector. The objective is to determine the classifier by calculating the values of $\mathbf{w}^T$ and b .

The function K for non-linearly separable data, also called the kernel function [112],

includes:

- Polynomial Kernel:

$$K(\mathbf{X}_i, \mathbf{X}_j) = (1 + \mathbf{X}_i^T \mathbf{X}_j)^p, \quad i = 1, \dots, N \quad (2.2)$$

This is a degree p polynomial kernel. $\mathbf{X}_i$ is on the margin.

- Gaussian Kernel:

$$K(\mathbf{X}_i, \mathbf{X}_j) = \exp\left(-\frac{\|\mathbf{X}_i - \mathbf{X}_j\|^2}{\sigma^2}\right) \quad (2.3)$$

After that, the classifier for the nonlinear SVM is represented by [113]:

$$F(x) = \sum_{a_i > 0} a_i y_i K(\mathbf{X}_i, \mathbf{X}_j) + b \quad (2.4)$$

where the Lagrangian multipliers are denoted by a , and $y_i \in \{-1, 1\}$.

2.7.2 Gaussian Process Regression (GPR)

Regression is a statistical method based on a training data set D with n input-output pairings that is used to predict a scalar output $\hat{y}^*$ associated with a D -dimensional input $\mathbf{x}^*$. Regression analysis often assumes that the observed outputs y_j are contaminated by additive Gaussian noise with constant variance σ_n^2 and produced by an unknown underlying function $f(\mathbf{x})$ [114]. This assumption can be stated mathematically as follows.

$$y_j = f(\mathbf{x}_j) + \varepsilon_j \quad (2.5)$$

where the noise term for each observation j is denoted by the variable ε_j , and the noise term is independently sampled from a Gaussian distribution with zero mean and variance σ_n^2 :

$$\varepsilon_j \sim \mathcal{N}(0, \sigma_n^2) \quad (2.6)$$

2.7.3 Artificial Neural Network (ANN)

The father of contemporary brain research, Santiago Ramón y Cajal, found around a century ago that neurons, or polarized cells that can receive and transmit information, make up the brain [115]. As shown in Figure 2.4, a biological neuron is composed of a cell body, dendrites, an axon, and synapses, which together enable information processing and communication within the brain.

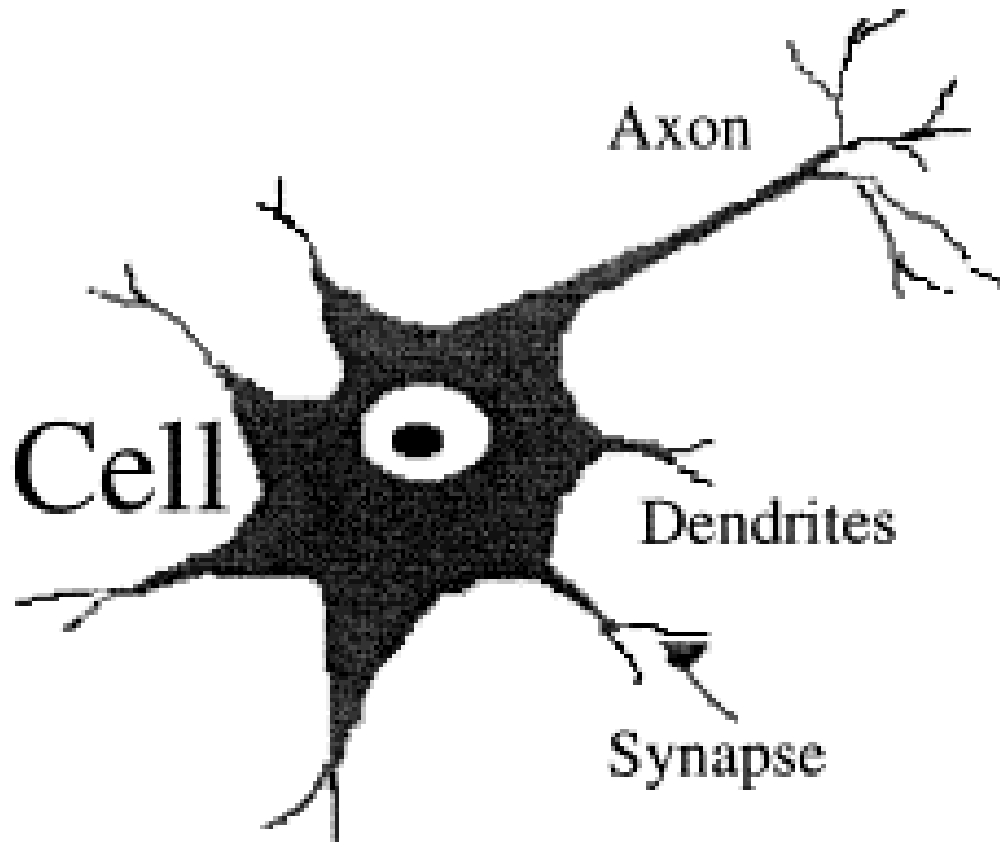


Figure 2.4: Biological neurons

The biological neural network is modeled by the artificial neural network (ANN), which is made up of linked nodes. It consists of three essential parts: learning rules, network topology, and node character. Signal processing is determined by the character of the node, whereas nodes are arranged and connected by the network structure. The weights are initialized and adjusted by the learning rules. The sections that follow provide a detailed explanation of each of these elements [116]

2.8 Neural Network Architectures

2.8.1 Single-Layer Perceptrons

Single-layer perceptrons are the simplest form of neural networks, consisting of a single layer of neurons [117, 118]. They are mainly used for binary classification problems. The architecture of a single layer perceptron, illustrated in Figure 2.5, shows how the inputs are linearly combined through weighted connections and a bias term, before passing through an activation function. The output of a single-layer perceptron can be expressed as follows:

$$y = f\left(\sum_{i=1}^n w_i x_i + b\right) \quad (2.7)$$

Where:

- y : Output
- f : Activation function (e.g., step function, sigmoid, ReLU, etc.)
- w_i : Weights applied to each input feature x_i
- x_i : Input features
- b : Bias term

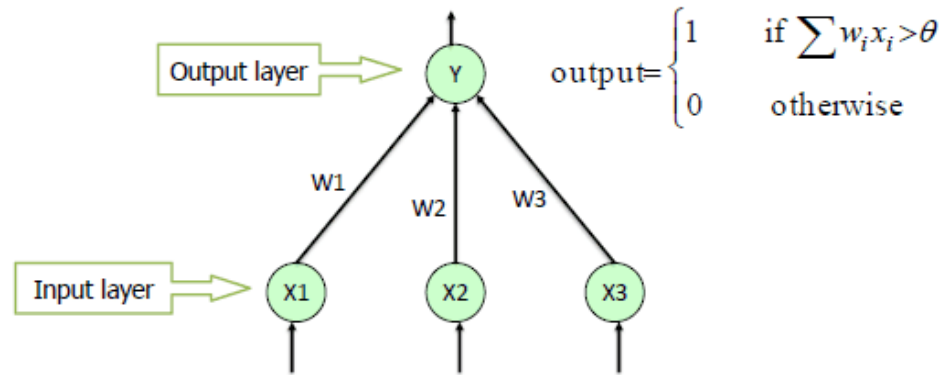
Single Layer Perceptron

Figure 2.5: Single Layer Perceptron Network

2.8.2 Multi-Layer Perceptrons (MLPs)

Multi-Layer Perceptrons (MLPs) include one or more hidden layers between the input and output layers [119]. These networks can model complex relationships between inputs and outputs, as illustrated in Figure 2.6.

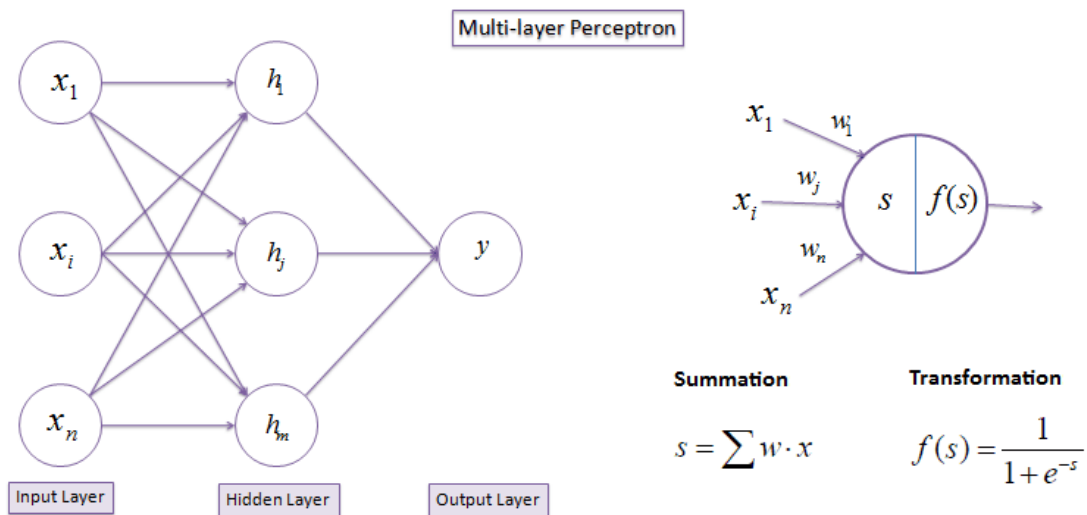


Figure 2.6: Multi-Layer Perceptron architecture.

The input of each neuron is the weighted sum of all inputs plus a bias:

$$s = \sum_{i=1}^n w_i x_i + b \quad (2.8)$$

Then a non-linear transformation is applied. For example, the sigmoid function is:

$$f(s) = \frac{1}{1 + e^{-s}} \quad (2.9)$$

The output of each hidden neuron is obtained by applying the activation function to the weighted inputs:

$$h_j = f\left(\sum_{i=1}^n w_{ij} x_i + b_j\right) \quad (2.10)$$

The final output is calculated as a weighted sum of hidden neurons passed through the activation function.

$$y = f\left(\sum_{j=1}^m v_j h_j + c\right) \quad (2.11)$$

Combining hidden and output layers (one hidden layer case), the general expression of an MLP is:

$$y = f\left(\sum_{j=1}^m v_j \cdot f\left(\sum_{i=1}^n w_{ij} x_i + b_j\right) + c\right) \quad (2.12)$$

2.8.3 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are specialized in processing grid-like data, such as images [120, 121]. They use convolutional layers to automatically learn spatial hierarchies of features. The convolution operation can be described as:

$$z_{li,j,k} = w_{lk}^T x_{li,j} + b_{lk} \quad (2.13)$$

where w_{lk} and b_{lk} are the weight vector and bias term of the k -th filter of the l -th layer, respectively. The kernel w_{lk} is shared between the $z_{li,:,k}$. The overall architecture of a CNN,

including convolutional, pooling, and fully connected layers, is illustrated in Figure 2.7.

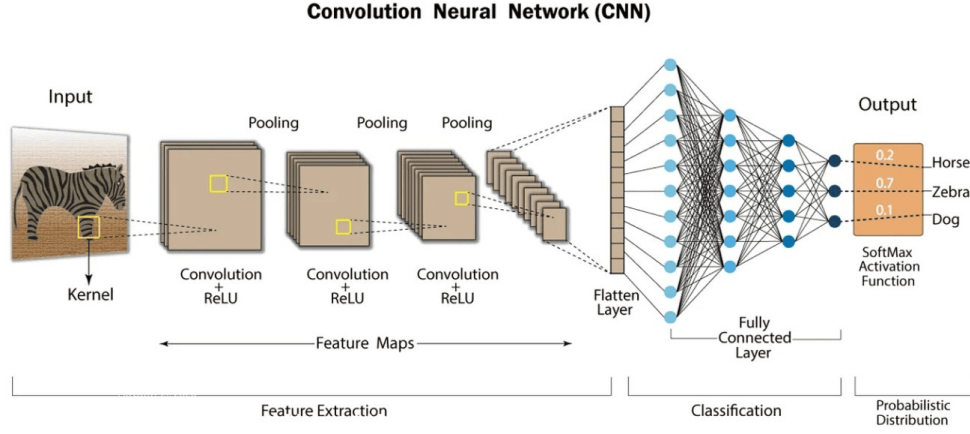


Figure 2.7: Convolutional Neural Network — CNN architecture

2.8.4 Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) [122] are designed for sequential data, such as time series or natural language. They use feedback connections to capture temporal dependencies. The output of an RNN can be expressed as [123]:

$$h_t = f(W_h h_{t-1} + W_x x_t + b_h) \quad (2.14)$$

where h_t is the hidden state at time t , W_h and W_x are weight matrices, x_t is the input at time t , and b_h is the bias. The structure of an RNN, showing how hidden states are recurrently connected across time steps to process sequential inputs, is illustrated in Figure 2.8.

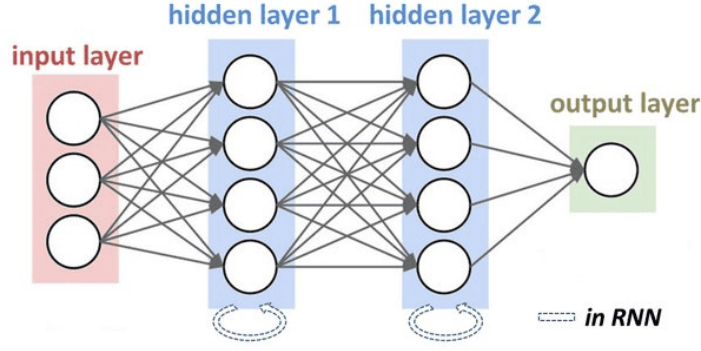


Figure 2.8: Recurrent Neural Networks

2.8.5 Long Short-Term Memory (LSTM) Networks

Long-Short-Term Memory (LSTM) networks are a type of RNN designed to address the vanishing gradient problem, allowing them to learn long-term dependencies in sequential data. The LSTM unit consists of gates that regulate the flow of information [124]:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2.15)$$

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (2.16)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (2.17)$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (2.18)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (2.19)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (2.20)$$

where σ denotes the sigmoid function and $\tanh$ is the hyperbolic tangent function. The internal structure of an LSTM cell, showing the input, forget and output gates that control the flow of information through the memory cell, is illustrated in Figure 2.9.

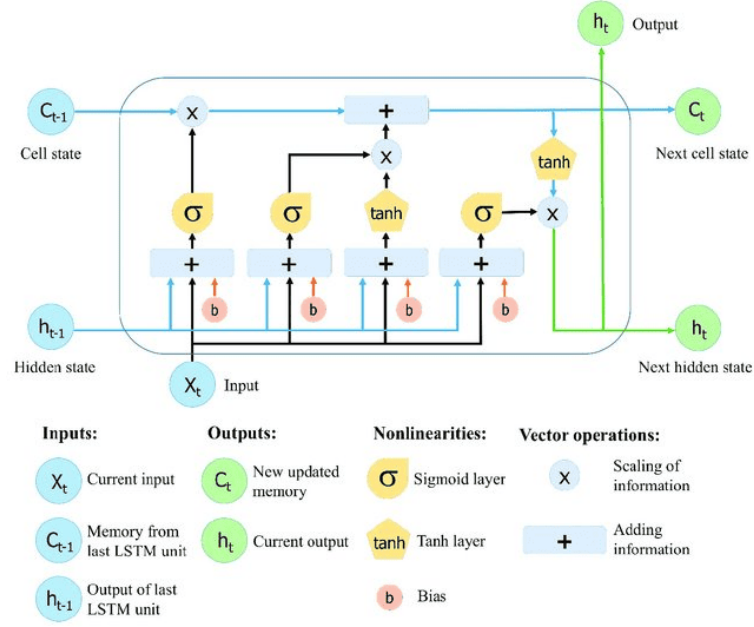


Figure 2.9: Long Short-Term Memory

2.8.6 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) consist of two neural networks, a generator, and a discriminator, competing against each other. The generator creates data samples, while the discriminator evaluates their authenticity [125]. The objective functions for GANs are:

$$\min_G \max_D \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (2.21)$$

where D is the discriminator, G is the generator, p_{data} is the data distribution, and p_z is the noise distribution. The interaction between these two networks, where the generator attempts to produce realistic data while the discriminator distinguishes between real and fake samples, is illustrated in Figure 2.10.

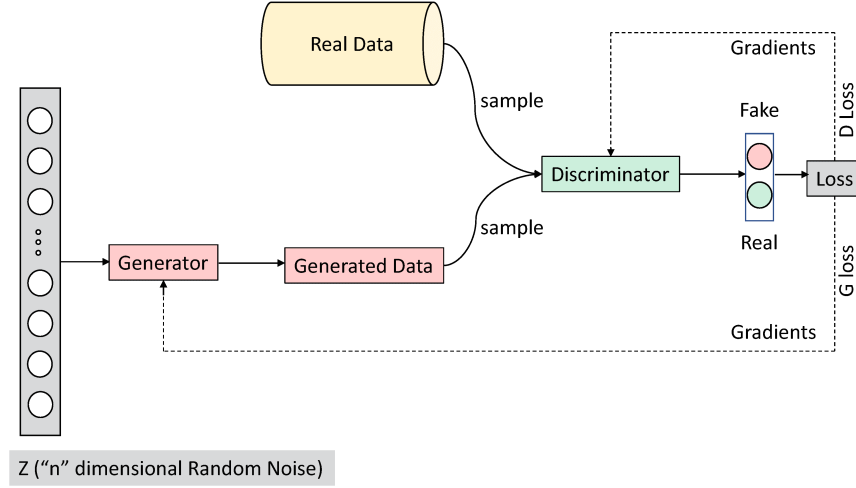


Figure 2.10: Generative Adversarial Network Architecture.

2.9 Working Principles of ANNs

2.9.1 Neuron Model

The neuron model in an ANN mimics biological neurons by taking inputs, applying weights, summing them up, and passing the result through an activation function. Mathematically:

$$y = f\left(\sum_{i=1}^n w_i x_i + b\right) \quad (2.22)$$

where f is the activation function.

2.9.2 Activation Functions

Activation functions introduce non-linearity into the network, allowing it to learn complex patterns. Common activation functions include

- **Sigmoid Function:**

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (2.23)$$

The sigmoid function maps input values into the range $[0, 1]$, making it useful for probabilistic interpretations. Its characteristic S-shaped curve is shown in Figure 2.11.

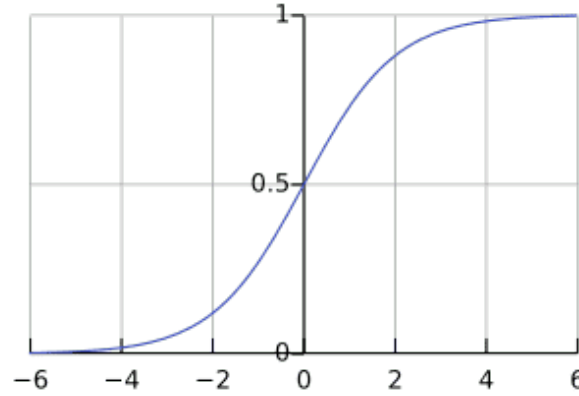


Figure 2.11: Sigmoid Function.

- **Hyperbolic Tangent (tanh) Function:**

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (2.24)$$

The tanh function maps inputs into the range $[-1, 1]$, making it zero-centered and often preferred over the sigmoid. Its curve is illustrated in Figure 2.12.

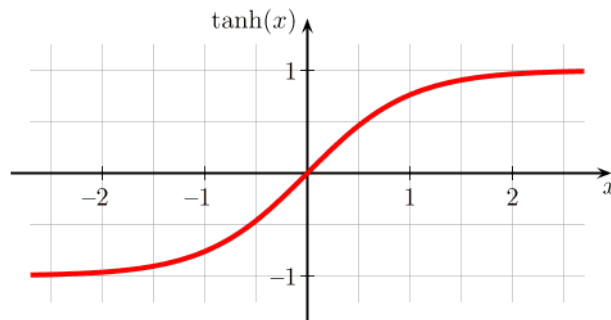


Figure 2.12: Hyperbolic Tangent (tanh) Function.

- **Rectified Linear Unit (ReLU) Function:**

$$\text{ReLU}(x) = \max(0, x) \quad (2.25)$$

The ReLU function outputs zero for negative inputs and passes positive values unchanged, introducing sparsity and reducing vanishing gradient problems. Its behavior

is depicted in Figure 2.13.

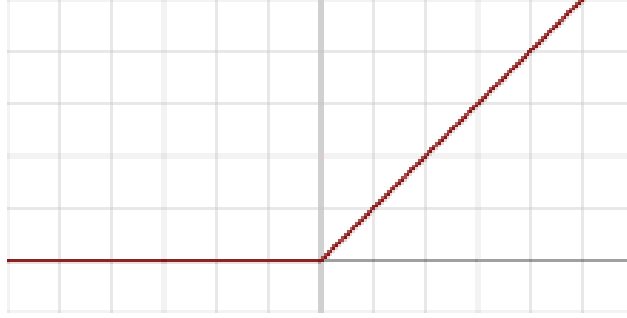


Figure 2.13: Rectified Linear Unit (ReLU) Function.

2.9.3 Mean Squared Error (MSE) in Artificial Neural Networks

Mean Squared Error (MSE) is a critical performance metric used in the training and evaluation of Artificial Neural Networks (ANNs). Measures the average square difference between the actual output values and the predicted output values generated by the network. During the training process, MSE is often utilized as the loss function that the network aims to minimize through backpropagation. The MSE is calculated using the formula [126]:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (2.26)$$

where N is the total number of data points, y_i represents the true output for the i -th data point, and $\hat{y}_i$ is the ANN's predicted output for that data point. The squaring of differences ensures that positive and negative errors do not cancel each other out and emphasizes larger discrepancies. One of the benefits of using MSE is its sensitivity to errors; it heavily penalizes larger errors, making it suitable for applications where significant discrepancies are particularly undesirable. Additionally, the smooth nature of the MSE function allows efficient gradient descent optimization, which is essential for ANN training. However, MSE can be sensitive to outliers, potentially skewing the overall error measurement. In cases where outliers are significant, alternatives like Mean Absolute Error (MAE) or Huber loss may be

considered. MSE is commonly applied in various ANN applications, such as regression tasks and time-series prediction, where accurate continuous output is required. By providing a clear target for optimization, MSE plays a vital role in the performance and reliability of neural network models.

2.9.4 Backpropagation Algorithm

The backpropagation algorithm is used to train neural networks by updating the weights based on the error gradient [127]. It involves computing the gradient of the loss function with respect to each weight through the chain rule:

$$\frac{\partial L}{\partial W^l} = \frac{\partial L}{\partial a^L} \cdot \frac{\partial a^L}{\partial z^L} \cdot \frac{\partial z^L}{\partial W^l} \quad (2.27)$$

where L is the loss function, a^L is the activation of the output layer, and z^L is the weighted input to the output layer.

2.9.4.1 Forward Propagation

Forward propagation involves passing input data through the network to obtain predictions. The output of each layer is calculated by applying the activation function to the weighted sum of its inputs [128]:

$$a^l = f(W^l a^{l-1} + b^l) \quad (2.28)$$

where a^l is the activation at layer l , W^l is the weight matrix, and b^l is the bias vector.

2.9.5 Gradient Descent Optimization

Gradient descent is an optimization technique used to minimize the loss function by iteratively adjusting the network weights in the direction of the steepest descent [129]:

$$W \leftarrow W - \eta \frac{\partial L}{\partial W} \quad (2.29)$$

where η is the learning rate.

2.10 Training and Learning in ANNs

2.10.1 Supervised Learning

In supervised learning, the network is trained using labeled data, where the correct output is known. The network learns to map inputs to outputs by minimizing the difference between predicted and actual values:

$$L = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (2.30)$$

where y_i is the actual output, $\hat{y}_i$ is the predicted output and N is the number of samples.

2.10.2 Unsupervised Learning

Unsupervised learning involves training the network with unlabeled data. The network learns to identify patterns and structures in the data without explicit output targets. Common techniques include clustering and dimensionality reduction.

2.10.3 Reinforcement Learning

Reinforcement learning is a type of learning in which the network learns to make decisions by receiving rewards or penalties based on its actions. The goal is to maximize the cumulative reward.

$$R = \sum_{t=0}^T \gamma^t r_t \quad (2.31)$$

where r_t is the reward at time t and γ is the discount factor.

2.10.4 Training Strategies and Algorithms

Various strategies and algorithms are used to train neural networks effectively. These include different optimization techniques and learning algorithms such as [130]:

- Gradient Descent (GD)
- Gradient Descent with Momentum (GDM)
- Gradient Descent with Adaptive Learning Rate (GDA)
- Conjugate Gradient (Fletcher-Reeves and Polak-Ribiere)
- Quasi-Newton (BFGS)
- Levenberg-Marquardt (LM)
- Bayesian Regularization

2.11 Antenna Optimization Using Artificial Neural Networks

The application of artificial neural networks (ANN) in antenna optimization offers a powerful alternative to traditional design methods. In this context, optimization refers to the process of finding an optimal combination of inputs that results in the best performance for an antenna design. This may involve maximizing gain, minimizing reflection, or balancing

multiple objectives such as size and efficiency. ANNs provide a flexible and efficient approach to achieving these goals by learning from data and making predictions about antenna performance.

Designing antennas through conventional methods can be time-consuming and often requires extensive trial-and-error or heuristic adjustments. The complexity of modern antennas, particularly those used in biomedical applications, makes it difficult to identify optimal configurations manually. This is where ANN-based optimization becomes valuable. By training a neural network on simulation data, the model can predict the performance of different antenna designs without the need for exhaustive simulation runs, significantly reducing the development time.

2.11.1 Single-Objective Optimization

Single-objective optimization focuses on improving a single performance metric, such as gain or bandwidth. In the context of antennas, this often involves maximizing the efficiency of a particular parameter while adhering to design constraints. ANNs can streamline this process by rapidly evaluating the impact of design changes, allowing engineers to fine-tune antenna characteristics with greater precision [131].

In practice, single-objective optimization is often extended to include constraints. For example, while maximizing gain, the design must also meet size or material limitations. ANNs can incorporate these constraints by learning from training data that includes such limitations, ensuring that the final design is both optimal and feasible.

2.11.2 Multi-Objective Optimization

Many antenna design problems involve trade-offs between multiple objectives [132], such as maximizing gain while minimizing size or operating over multiple frequency bands [133–135]. Multi-objective optimization addresses this by generating a set of potential solutions that

represent different trade-offs between these competing goals. These solutions form what is known as the Pareto front, where no single solution is strictly better than another across all objectives.

ANNs are particularly well suited for multi-objective optimization, as they can be trained to predict multiple performance metrics simultaneously. Using ANN-based models, engineers can explore a wide design space and identify promising solutions that balance different performance requirements. Once the Pareto front is identified, a decision-making process can select the most appropriate design based on the specific needs of the application.

2.11.3 Variable-Fidelity Optimization

Variable fidelity optimization (VFO) combines high- and low-fidelity models to optimize antenna designs more efficiently [109, 136]. High-fidelity models, such as full-wave electromagnetic simulations, provide precise results but are computationally expensive. Low-fidelity models, while less accurate, can be evaluated much faster. VFO techniques leverage both, using low-fidelity models to explore the design space and high-fidelity models to refine the most promising solutions.

In ANN-assisted VFO, the neural network serves as a surrogate for the high-fidelity model, providing fast approximations of antenna performance. This allows rapid iteration during the optimization process, with only a few high-fidelity simulations needed to validate the final design. This approach can dramatically reduce computational costs while maintaining a high level of accuracy.

2.11.4 Multilayer ANN-Assisted Optimization

In more complex design scenarios, multilayer ANNs can be employed to handle various stages of the optimization process. These networks, which consist of multiple layers of neurons, are able to model highly non-linear relationships between input parameters and performance

metrics. This makes them well suited for optimizing advanced antenna designs, such as those that operate over multiple frequency bands or have intricate geometries [5, 109, 137].

By incorporating ANN models into different stages of the design process, such as worst-case analysis and robustness testing, engineers can ensure that the final antenna design meets all performance requirements under varying conditions. This is especially important in biomedical applications, where the antenna must function reliably in the presence of different tissue types and varying operating environments.

2.11.5 Surrogate-Based Optimization

Finally, surrogate models, including those based on ANNs, are increasingly being used to reduce the computational burden of antenna optimization. Instead of relying solely on expensive electromagnetic simulations, these models approximate the performance of a given design based on a limited set of training data. Once trained, the surrogate model can predict the behavior of new designs with minimal computational effort.

ANN-based surrogate models are particularly effective in situations where the design space is large and the number of possible configurations is large. By training the ANN on a representative set of simulations, the model can generalize to predict the performance of new designs without need for further simulation, allowing for faster and more efficient optimization [138, 139].

2.12 Antenna using Artificial Neural Networks

In recent years, the use of Artificial Neural Networks (ANNs) has become a crucial tool in antenna design and performance optimization, due to their ability to handle complex and non-linear relationships between design parameters and antenna responses. Initially, conventional neural networks, such as feedforward backpropagation neural networks, were used

to accelerate the modeling process and predict electromagnetic properties based on the geometrical and material inputs of the antenna [8, 9]. As demand for higher accuracy and faster processing increased, more advanced models such as Generalized Regression Neural Networks (GRNN) were introduced, demonstrating superior performance, particularly with small datasets, and significantly reducing training time while maintaining prediction precision [140]. Subsequently, to achieve improved and more efficient antenna designs, researchers began integrating ANNs with intelligent optimization algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) [7]. In these hybrid approaches, the ANN rapidly estimates performance values, while the optimization algorithms search for the best set of antenna parameters. In communication applications, it has become necessary to simultaneously optimize multiple objectives, such as gain, bandwidth, radiation efficiency, and antenna size. Artificial Neural Networks (ANNs) have proven to be a powerful tool for handling multi-objective optimization problems independently, without the need for external optimization algorithms. By training ANNs on datasets that represent various trade-offs between conflicting performance metrics, these networks are able to predict and balance multiple objectives simultaneously. Through careful design of the training process and appropriate selection of input-output mappings, ANNs can approximate the Pareto front directly, offering designers a range of optimal solutions that satisfy different design criteria. This capability highlights the flexibility and efficiency of neural networks in addressing complex antenna design challenges and emphasizes their growing role in the development of high-performance multi-objective-optimized antenna systems [133].

2.13 Conclusion

This chapter reviewed the foundations of Machine Learning and its relevance to antenna design and optimization. Key concepts such as the distinction between AI, ML, and DL, as well as the categories of supervised, unsupervised, and reinforcement learning, were explained. Algorithms including SVM, GPR, and ANN were introduced, with ANN receiving particular attention due to its strong capability in modeling complex, nonlinear relationships.

The analysis highlighted how ML techniques can reduce computational costs, improve prediction accuracy, and enable more efficient exploration of design spaces compared to traditional electromagnetic simulations. These advantages make ML an attractive approach for solving optimization problems in biomedical antenna design.

Building on this foundation, the next chapter will focus exclusively on Artificial Neural Networks, exploring their architectures, training strategies, and applications in practical antenna optimization problems.

Chapter 3

Artificial Neural Networks for Antenna Optimization

3.1 introduction

Following the general overview of Machine Learning techniques in the previous chapter, this chapter focuses specifically on Artificial Neural Networks (ANNs) and their application to antenna design and optimization. ANNs are computational models inspired by the structure and learning processes of the human brain, well suited to solving complex nonlinear problems such as electromagnetic modeling.

The chapter begins by reviewing the working principles of ANNs, including neuron models, activation functions, training strategies, and performance metrics such as Mean Squared Error (MSE). A comparison of learning algorithms, particularly Feedforward Backpropagation Networks (FFBPN) and General Regression Neural Networks (GRNN), is then presented to evaluate their suitability for antenna design.

To demonstrate the practical relevance of ANNs, several case studies are introduced. These include the optimization of a circular slotted patch antenna, the design of ultra-wideband (UWB) antennas, and the development of a dual-band antenna operating at 2.45/5.8 GHz for biomedical applications.

Through these studies, the chapter highlights the advantages of ANN-based models in predicting antenna characteristics with high accuracy while significantly reducing design time compared to traditional electromagnetic simulations.

3.2 Analysis of the Learning Algorithms Performance

Table 3.1 presents the performance of different learning algorithms in terms of training time, mean squared error (MSE) and root mean squared error (RMSE). All algorithms were trained using a neural network architecture with three hidden layers containing [10, 10, 15] neurons, respectively. The Levenberg-Marquardt (LM) algorithm is observed to have the best performance, recording the lowest MSE (1.5×10^{-6}) and RMSE (0.0012) with a moderate training time. Similarly, the Bayesian regularization (BR) algorithm demonstrated comparable accuracy with a slightly higher training time. However, algorithms based on Gradient Descent (GD) exhibited poorer performance, reflected by higher MSE and RMSE values despite their shorter training times. Overall, a trade-off between accuracy and training time can be observed: algorithms like LM and BR offer high precision at the cost of longer training durations, while algorithms such as GD prioritize faster training at the expense of accuracy. Based on these results, the Levenberg-Marquardt (LM) algorithm will be adopted in all future studies because of its superior accuracy and reliable performance.

Table 3.1: Performance obtained in learning algorithms

Algorithms	Time (mm:ss)	MSE	RMSE
LM	0:02:56	1.5×10^{-6}	0.0012
OSS	0:01:31	0.0012	0.0347
BFG	0:01:21	7.6×10^{-4}	0.0276
SCG	0:00:53	2.89×10^{-4}	0.0170
RPROP	0:00:24	0.0012	0.0343
BR	0:04:01	1.85×10^{-6}	0.0014
GD with adaptive	0:00:16	0.0039	0.0627
GD with momentum	0:00:17	0.0192	0.1389
GD	0:00:17	0.0130	0.1140

3.3 Optimization of a circular slotted patch with a defected grounded monopole patch antenna using artificial neural networks

3.3.1 Antenna Design

The antenna suggested is designed using the high frequency structure simulator (HFSS) [141]. Figure 3.1 illustrates a construction featuring a circular inscribed groove within a rectangular patch, affixed to an FR-4 substrate with a relative permittivity of 4.4 and a thickness of 1.5 mm. The conductive components are made up of copper with a thickness of 0.035 mm. Table 3.2 summarizes all dimensions. The next section will assess the prediction and optimization capabilities of the ANN model.

Table 3.2: Antenna Dimensions

Parameter	Dimension (mm)	Parameter	Dimension (mm)
WP	30	LG	4.5
LP	25	Wsub	60
WF	2.9	Lsub	70
LF	21	R	10
Y	5.5	X	6.5
GB	19.5	G	1.5
S	5	GT	6
WG	3.9	GX	7

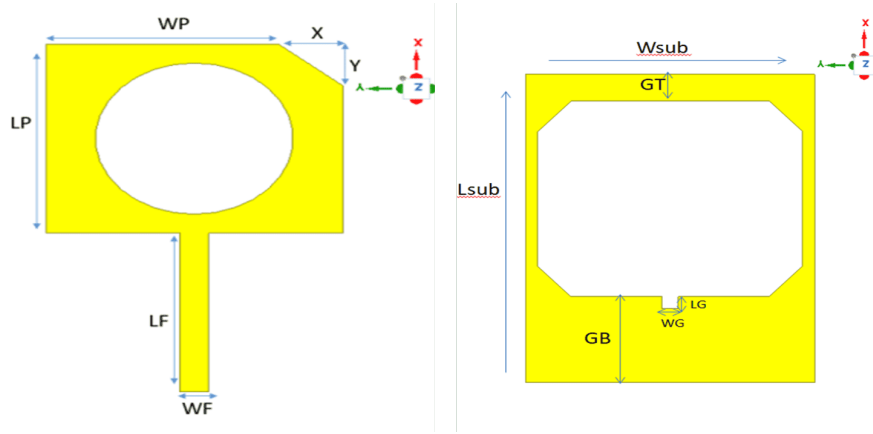


Figure 3.1: Front View and Back View of the Proposed Antenna in HFSS.

3.3.2 ANN Model

This study utilises a feed-forward Multi-Layer Perceptron (MLP) neural network design. The model is trained using simulation data produced by HFSS. The input parameters encompass the antenna's physical dimensions, and the output parameters denote performance measurements like return loss and resonant frequency. The dataset was partitioned into training, validation, and testing subsets. The artificial neural network (ANN) was created in MATLAB using the Levenberg-Marquardt (LM) algorithm for training because it is faster and more accurate, as supported by relevant studies (see Chapter 3, Section 3.2). Figure 3.2 illustrates the ANN structure used in this study.

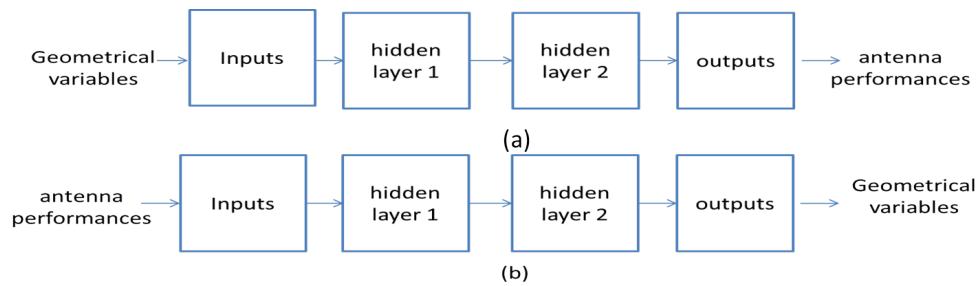


Figure 3.2: (a) Analysis and (b) Synthesis Models of Neural Networks for Antenna Design.

To prepare the dataset, each geometric variable (G1, LG, S, WG) was systematically varied within the specific limits summarized in Table 3.3. These variations were performed

to generate a comprehensive dataset that captures the impact of the geometrical parameters on the antenna performance, particularly on the return loss (S_{11}).

Table 3.3: Parametric Study

Geometrical Variables	Min	Max	Step
G1	-1.5 mm	4 mm	1 mm
LG	2.5 mm	7 mm	1 mm
S	2 mm	7 mm	1 mm
WG	2.4 mm	5.85 mm	1 mm

3.3.3 Results and Discussion

3.3.3.1 Analysis ANN models

Figure 3.3 illustrates a comparison between the simulated values obtained from HFSS (red) and the values predicted by the ANN model (blue) for several sets of input parameters. Each Figure 3.3 (a), (b), and (c) corresponds to a distinct configuration of the geometrical parameters $G1$, LG , S , and WG . The reflection coefficient S_{11} is plotted as a function of frequency, showing that the ANN model accurately reproduces the antenna performance. The ANN predictions closely follow the HFSS curves, with only minor deviations near certain resonance frequencies; these small differences are likely due to the nonlinear electromagnetic behavior around resonance and the sensitivity of S_{11} to slight geometric variations.

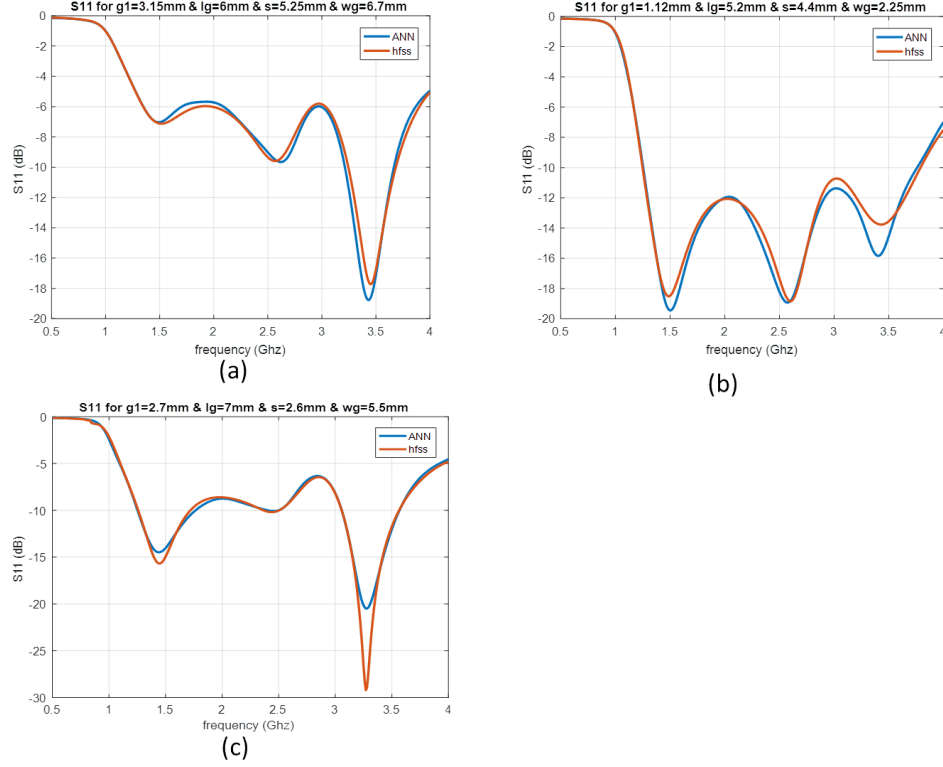


Figure 3.3: Comparison of results obtained using HFSS and MATLAB-ANN analysis model.

3.3.3.2 The synthesis ANN model

Figure 3.4 used the synthesized model depicted in Figure 3.2(b), to forecast the antenna dimensions ($G1$, LG , S , WG) according to the specified operating frequency and reflection coefficient. To assess the suggested model, the geometric variables are presented as follows:

$$T1_{\text{Target}} = [-0.5, 2.8, 3.9, 5.5]$$

$$T2_{\text{Target}} = [3, 6.65, 4.97, 3.88]$$

$$T3_{\text{Target}} = [1.65, 4.78, 2.9, 3.7]$$

The obtained geometrical variables are:

$$T1_{\text{Proposed}} = [0.1601, 4.9132, 4.0547, 4.3015]$$

$$T2_{\text{Proposed}} = [2.5500, 4.7561, 4.3013, 4.1839]$$

$$T3_{\text{Proposed}} = [2.0991, 4.8410, 4.1369, 4.2733]$$

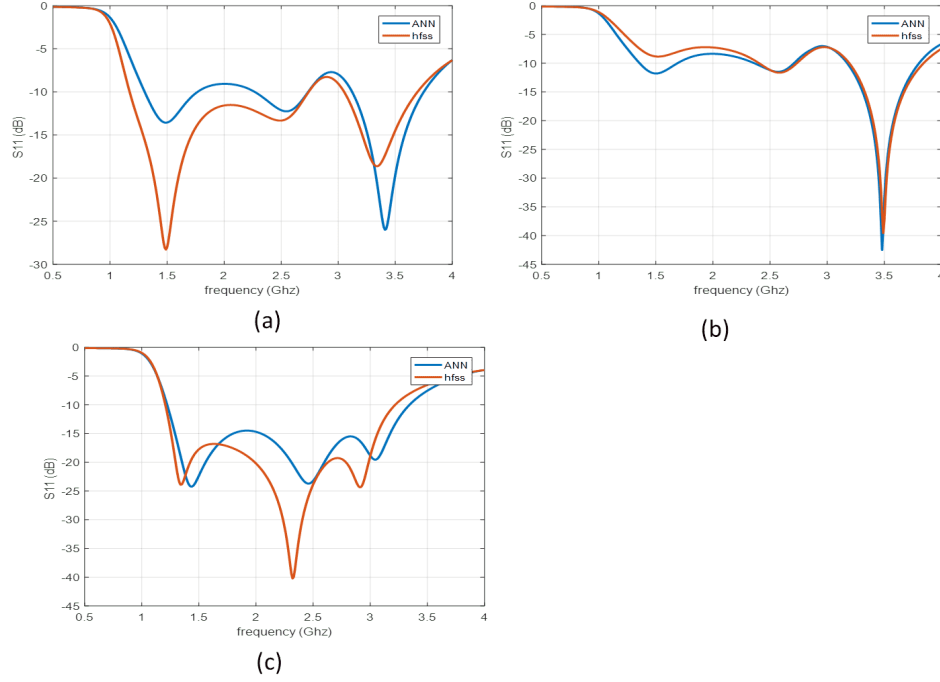


Figure 3.4: Comparison of results obtained using HFSS and MATLAB-ANN synthesis model

In the following section, the work will progress with the addition of specific rules and limits to the ANN models to create antennas that work well for ultra-wideband (UWB) uses, especially in medicine. Special attention will be paid to achieving reliable performance around specific frequency bands, such as 5.8 GHz, which are crucial for certain medical communication applications. This sequential approach ensures a gradual transition from general optimization to more application-specific and high-performance antenna designs.

3.4 Optimization of UWB Antennas Using Artificial Neural Networks (ANN)

3.4.1 Antenna Design

This section presents specific examples of UWB antenna designs optimized using the proposed ANN method [82]. Each example includes the antenna structure, dimensions, performance metrics, and the results of the optimization process.

The antenna structure for biomedical applications is shown in Figure 3.5. In the design, an FR-4 substrate with a relative dielectric permittivity of 4.4 and a thickness of 1.6 mm is used.

The antenna design dimensions are listed in Table 3.4. The performance necessary to achieve this in the designated frequency bands depends on these dimensions.

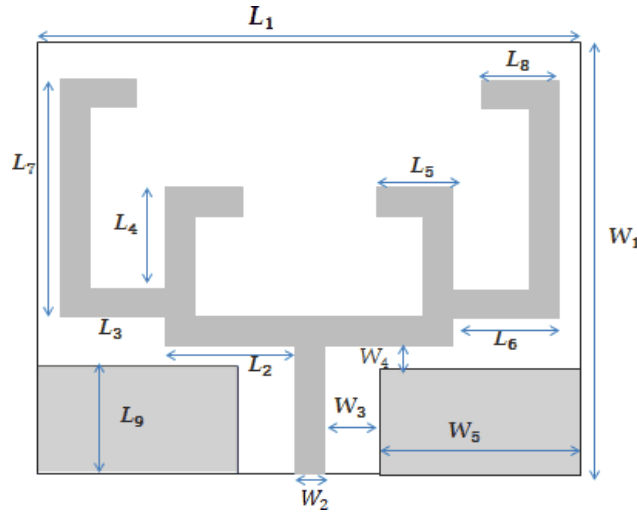


Figure 3.5: Structure of Antenna

3.4.2 ANN Model

In this study, as explained in Section 3.3.2, we created an artificial neural network (ANN) model to predict five shape measurements (L_4 , L_5 , L_6 , L_7 , and L_8) based on the input reflection coefficient (S_{11}). The goal was to design an antenna that operates specifically at 5.8

Table 3.4: Antenna Size Parameters for antenna Design

Parameter	Dimension (mm)
W_1	44
W_2	3
W_3	0.5
W_4	0.5
W_5	22
L_1	48
L_2	10.5
L_3	8
L_9	12
H	1.6

GHz within the Ultra-Wideband (UWB) range while maintaining a reflection coefficient (S_{11}) below -10 dB across the targeted band. To make sure it works well, the network was trained using the Levenberg-Marquardt (LM) algorithm, which was explained earlier in Section 3.2, where we talked about why we chose LM for all studies. The neural network architecture consisted of a single hidden layer comprising 10 neurons. The training data set used for this synthesis process, including the defined ranges and step sizes of the geometrical variables, is summarized in Table 3.5. This data set allowed the network to efficiently learn the relationship between the desired antenna performance and the optimized geometric parameters.

Table 3.5: Training Data for Geometrical Variables

Geometrical Variable	Min (mm)	Max (mm)	Step (mm)
L_4	3.4	9	2
L_5	3.4	12	2
L_6	3.4	12	2
L_7	14	22	2
L_8	3.5	7	2

3.4.3 Results and Discussion

Figure 3.6 presents a comparison between the actual S_{11} values obtained from HFSS simulations and those predicted by the ANN model. Each blue circle represents a single data

sample, while the red marker indicates the optimal result corresponding to the design condition at 5.8 GHz for UWB antenna operation. The strong clustering of points along the diagonal line demonstrates a high correlation between the predicted and simulated values, confirming that the ANN model accurately learns the nonlinear relationship between the geometrical parameters and the antenna reflection coefficient. The small deviations observed for a few samples are mainly attributed to nonlinear variations near resonance and the limited training data in those regions.

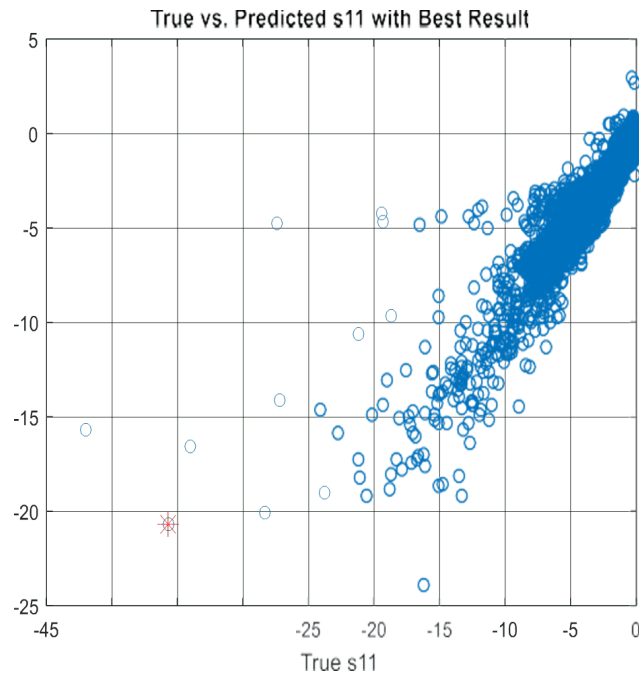


Figure 3.6: Comparison of True vs. Predicted S_{11} Values for Optimized Antenna Design Using ANN

The reflection coefficient (S_{11}) of the optimized ultra-wideband (UWB) antenna is illustrated in Figure 3.7. The antenna resonates at 5.8 GHz, with a minimum S_{11} value of approximately -20.49 dB. The $|S_{11}|$ value remaining below -10 dB across the frequency range from 5.17 GHz to 7.02 GHz confirms that the antenna effectively covers the UWB spectrum while also operating efficiently at the Industrial, Scientific, and Medical (ISM) band centered at 5.8 GHz. This wide impedance bandwidth ensures low reflection and excellent impedance

matching between the antenna and the feeding network.

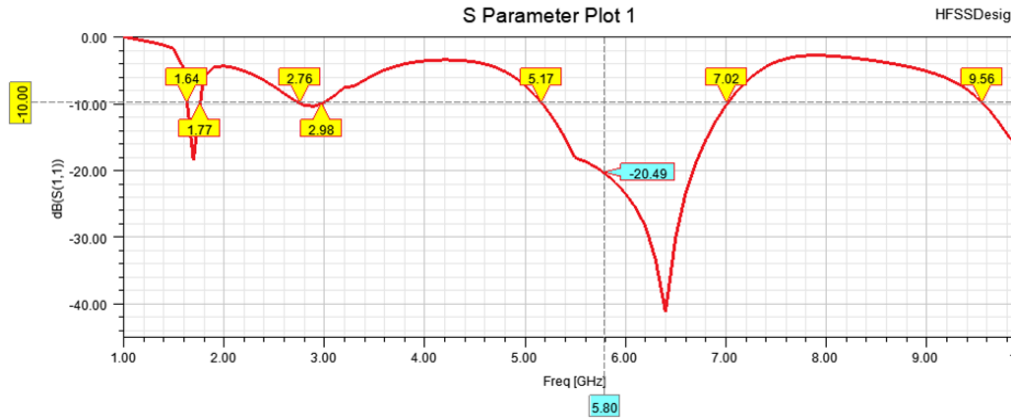


Figure 3.7: Reflection Coefficient of the Proposed Antenna

In the next section, a different antenna structure was investigated and the particle swarm optimization (PSO) algorithm was introduced to extract an explicit analytical model linking the antenna input parameters to its performance. Since artificial neural networks (ANNs) do not inherently provide a direct function, PSO was utilized to overcome this limitation. In addition to PSO, a detailed performance analysis was performed on two types of neural network: the feedforward backpropagation neural network (FFBPN) and the general regression neural network (GRNN) without direct comparison with PSO. This represents a new direction compared to previous studies. Furthermore, the function extracted from the PSO process enables easy replication and application of the antenna design by other users, without the need to retrain a neural network model.

3.5 ANN and PSO Based Design of Dual Band Antenna for 2.45/5.8 GHz ISM band Medical Applications

3.5.1 Antenna Design

Fig 3.8 depicts the geometric arrangement of the dual-band planar antenna, which operates at frequencies of 2.45 and 5.8 GHz. This antenna is composed of three planes: the radiating plane, the substrate plane, and the ground plane. The F-shaped element that emits radiation is attached to a substrate made of FR-4. The FR-4 substrate has specific properties, including a dielectric constant of 4.3, a thickness of 1.6 mm, and a loss tangent of 0.019.

A truncated ground plane is used to attain the appropriate bandwidth and radiation properties. A microstrip feed line with a width of 3 mm and a characteristic impedance of 50Ω is built using the principles of standard transmission line theory [142]. The antenna is stimulated by an SMA port that is connected to the feed line.

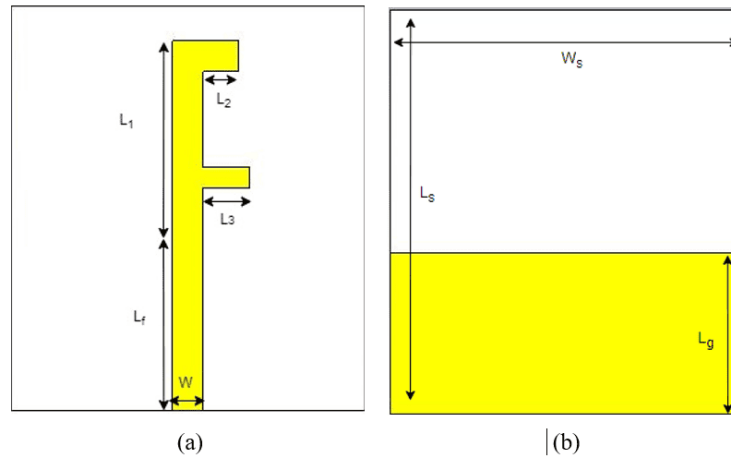


Figure 3.8: Various geometrical views of the proposed F-shape antenna: (a) front, (b) rear

3.5.2 Numerical Analysis

A planar monopole antenna was specifically designed to operate at frequencies of 2.45 and 5.8 GHz, with the intention of being used in ISM medical applications. The dimensions of the suggested design were established using the transmission line model [142, 143]. The effective dielectric constant (ε_{reff}) and the extension of the length were calculated using Eqs 3.1 and 3.2. The specifications of the proposed antenna are given in Table 3.6.

$$\varepsilon_{reff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2} \left(1 + 12 \frac{h}{w} \right)^{-0.5} \quad (3.1)$$

The symbol ε_r represents the dielectric constant, w represents the width of the radiating patch, and h represents the height of the substrate. The effective resonant lengths (lf values) are derived by computing the surface current distributions for the specific frequency modes. These lengths are approximately equivalent to one-quarter of the guided wavelength, specifically.

$$L_{\text{eff}} = \frac{v_0}{2f_r \sqrt{\varepsilon_{\text{reff}}}} \quad (3.2)$$

Table 3.6: The geometrical parameters of the proposed antenna

Parameters	Value (mm)	Parameters	Value (mm)
L_1	19	L_f	17.5
L_2	3.5	$W_s = W_g$	35
L_3	4.6	L_s	40
L_4	3	L_g	16
L_5	2	W	3

3.5.3 ANN Model

As discussed in Section 3.2, the performance of different learning algorithms was analyzed and the Levenberg-Marquardt (LM) algorithm was selected because of its superior accuracy.

This methodology was also adopted in Section 3.3.2, where the ANN model was trained using the LM algorithm, as illustrated in Table 3.1.

In this section, the same approach is applied to design the ANN model for the dual-band antenna. The dataset is generated using CST Microwave Studio, consisting of 120 randomly generated samples. Each sample includes the geometrical parameters of the antenna $X = \{x_1, x_2, x_3, x_4, \dots, x_n\}$ as inputs, with the corresponding resonant frequencies (f_{r1} and f_{r2}) as outputs. Of these samples, 84 are used for training, while 18 are reserved for testing and validation, ensuring a reliable evaluation of the model's performance.

3.5.4 CURVE FITTING APPROACH

The primary aim of this technique is to depict empirical data using a model, such as a function or a mathematical equation, and to assess the parameters linked to that model. In other words, it offers the most accurate representation of the experimental data using a mathematical model. Calculate the coefficient values that result in a function that closely approximates the given data set. This study employs a curve fitting method to establish a straightforward mathematical correlation between the parameter values L_2 and L_3 and the related operating frequencies (f_{r1} and f_{r2}). A data collection including 121 samples is randomly generated by selecting various parameters. Using this methodology, the subsequent pair of mathematical equations is produced. MATLAB software enables the creation of curves, surfaces, and mathematical functions through the process of curve fitting. This technique facilitates the establishment of a practical correlation between observed data and parameter values, resulting in optimal alignment with the data set. The primary methodologies for curve fitting are least-squares regression and interpolation. The current study uses the curve fitting technique to establish a correlation between the parameter values and the corresponding resonant frequencies (f_{r1} and f_{r2}). The data set is collected using the CST and MATLAB software. The

data set of 121 samples is obtained by systematically altering the parameter values L_2 and L_3 of the proposed antenna. The selected range of ' L_2 ' is 2.5 to 4.5 mm and ' L_3 ' is 3 to 5 mm. The resonant frequency corresponding to each sample is noted.

Based on this data set, we have derived the equations for fr_1 and fr_2 is given in eq. 3.3 and 3.4 .

$$fr_1 = -0.05375L_2 - 0.0007603L_3 + 2.638 \quad (3.3)$$

$$fr_2 = -0.09278L_2 - 0.345L_3 + 7.716 \quad (3.4)$$

3.5.5 Particle Swarm Optimization (PSO)

The particle swarm optimization (PSO) technique, first proposed by Kennedy and Eberhart [144], is characterized by its efficient use of the cooperative behavior exhibited by the particles. A set of particles with randomly assigned positions is defined in an N-dimensional design space. The positions of these particles are updated in each iteration based on velocity updates [145]. Once the position and velocity of each particle in the population have been set, it is necessary to update the velocity of each particle. To achieve the optimal outcome, it is necessary for each particle to modify its velocity [7]. During each iteration, every particle updates its position taking into account its current position, current velocity, the distance between its current position and its personal best position (pbest), and the distance between its current position and the global best position (gbest) [145].

The selection of the fitness or cost function is meticulously made to guarantee the optimal performance of the PSO algorithm. The design space and cost function are unique to the optimization problem. The PSO algorithm uses the following equations 3.5 and 3.6 to update the velocity and position of each particle [7] :

$$v_i(t+1) = wv_i(t) + c_1r_1 [pbest(t) - x_i(t)] + c_2r_2 [gbest(t) - x_i(t)] . \quad (3.5)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (3.6)$$

where v_i represents the velocity of the particle, x_i represents the position of the particle, w is the inertial weight, c_1 and c_2 are acceleration constants, both having a value of 1.5.

The algorithm concludes when a satisfactory solution is achieved. An objective function is formulated to ensure that the proposed antenna reaches resonance at frequencies specified by the user, as represented by the equation 3.7. Figure 3.9 displays the comprehensive flow diagram of the particle swarm optimization (PSO) algorithm used to calculate the parameter values L_2 and the peremeter value L_3 .

$$costfunction = \sqrt{(2.45 - fr_1)^2 + (5.8 - fr_2)^2} \quad (3.7)$$

3.5.6 Results and discussions

The evaluation of the antenna's performance is conducted through a thorough approach that encompasses the development, modeling, and analysis of its radiating structure using CST Microwave Studio 2014. When activated through a waveguide port, essential performance metrics such as directivity, VSWR, gain, reflection coefficient, surface electric field, and far-field pattern are evaluated.

By integrating open-add-space boundary conditions into the simulations, a comprehensive assessment of the antenna's performance and behavior is attained. This method offers a precise representation of how the antenna interacts with the surrounding environment. This methodology provides valuable insight into the effectiveness, focusing capability, and dis-

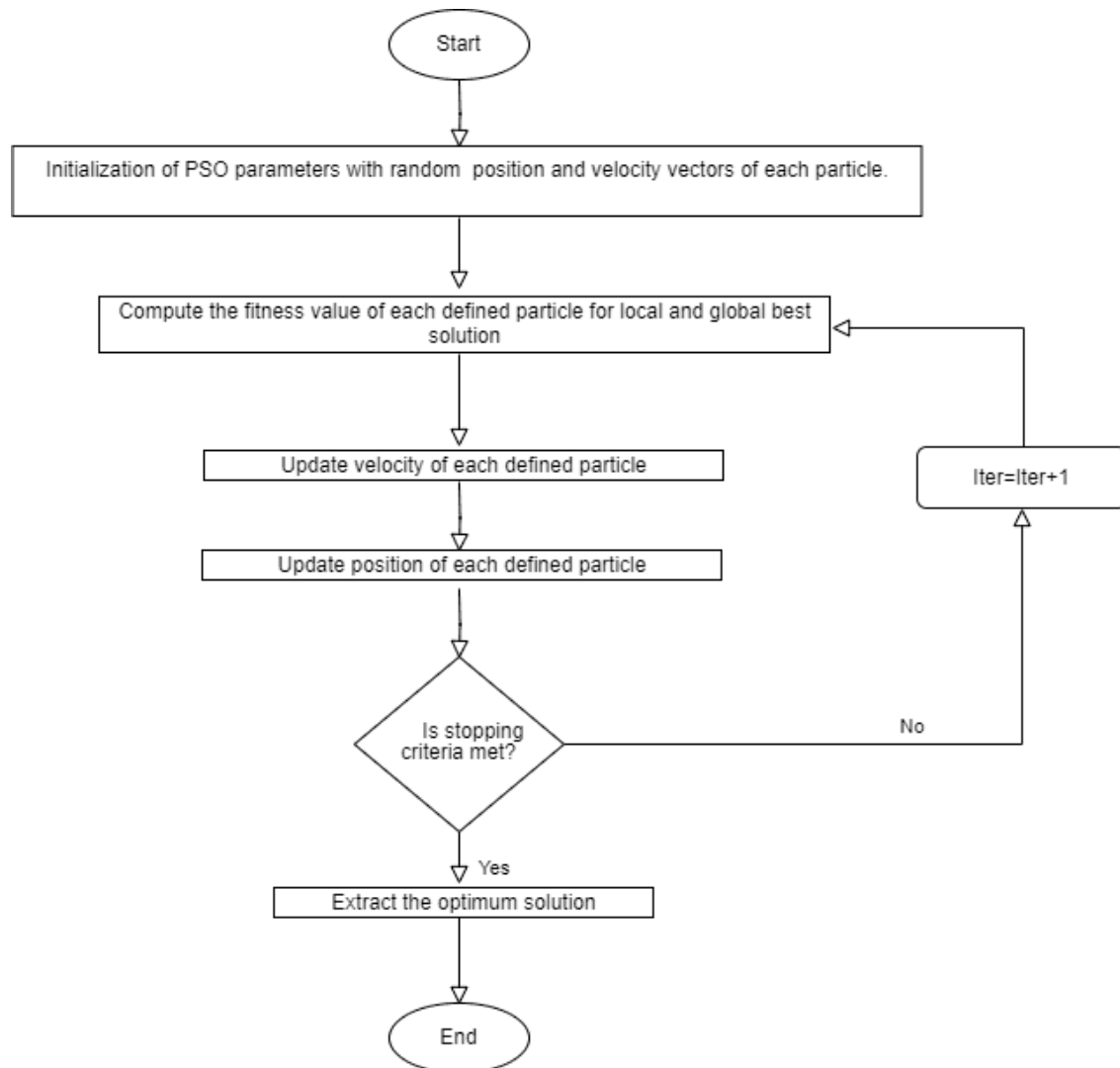


Figure 3.9: Detailed flow chart of PSO algorithm

persion of electromagnetic fields of the antenna, allowing for optimization based on specific design criteria.

3.5.6.1 Bandwidth and Scattering Parameters S11

The objective of the design being discussed is to achieve dual-band capabilities specifically for medical applications. This has been achieved by using an antenna design that features a modified radiation patch. Figure 3 compares the return loss characteristics of three different antennas: the rectangular monopole antenna (Figure 3.10 a), the antenna with an inverse-shaped radiating patch L (Figure 3.10 b) and the antenna with a modified F-shaped radiator (Figure 3.10 c).

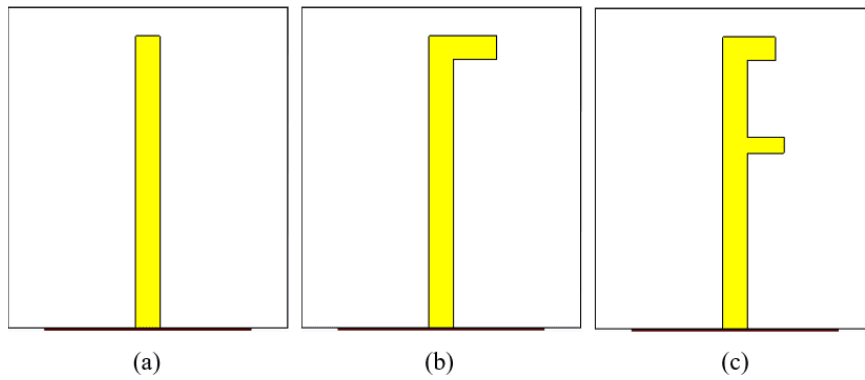


Figure 3.10: Antenna structure. (a) Base structure (b) L inverse-shaped (c) F-shaped

In order to assess the effectiveness of the suggested antenna, a frequency range spanning 1 to 9 GHz was chosen for analysis. The two frequency ranges of interest are 2.21 to 2.82 GHz and 5.61 to 6.01 GHz, with center frequencies of 2.448 and 5.8 GHz, respectively.

In the 1st design, the antenna resonates at 2.645 GHz and 7.3 GHz with $S(1,1)$ values of -24.4 dB and -11.99 dB, respectively, as shown in Fig. 3.11.

In the 2nd design, the antenna resonates at 2.33 GHz and 5.58 GHz with $S(1,1)$ values -25.445 dB and -18.95 dB, respectively. The proposed antenna operates within the ISM frequency bands, that is, (2.4-2.5 GHz) and (5.61–6.01 GHz).

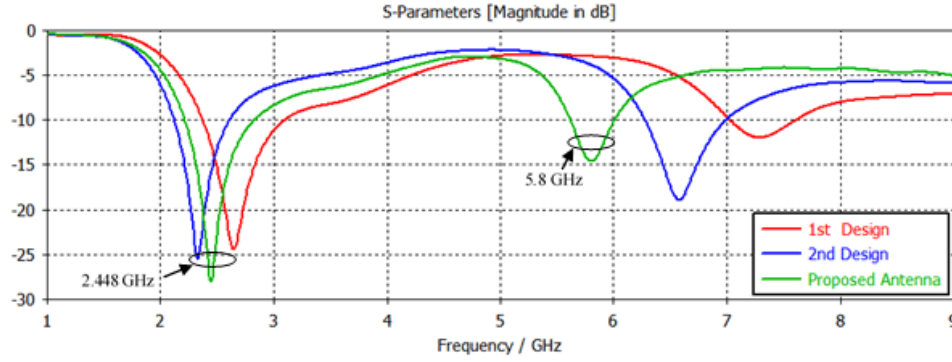


Figure 3.11: $S(1, 1)$ characteristics of first and second and proposed designs.

The S_{11} values of -27.97 dB and -14.63 dB measured at 2.48 GHz and 5.8 GHz represent the respective resonant frequencies. The bands utilize frequencies of 610 MHz (ranging from 2.21 to 2.82 GHz) and 400 MHz (ranging from 5.61 to 6.01 GHz). The specified bandwidth of 610 MHz is greater than the usual range of frequencies for the ISM band, which is from 2.4 to 2.4835 GHz. However, the 400 MHz bandwidth fits well within the higher frequencies of the ISM bands, which range from 5.725 to 5.875 GHz. These bands are designated for noncommunication uses; however, they can be used for communication within certain regulations, such as Wi-Fi, Bluetooth, and select cordless phones. Fig. 3.12 presents the simulated S_{11} characteristics of the proposed antenna, illustrating its return-loss performance across the operating band.

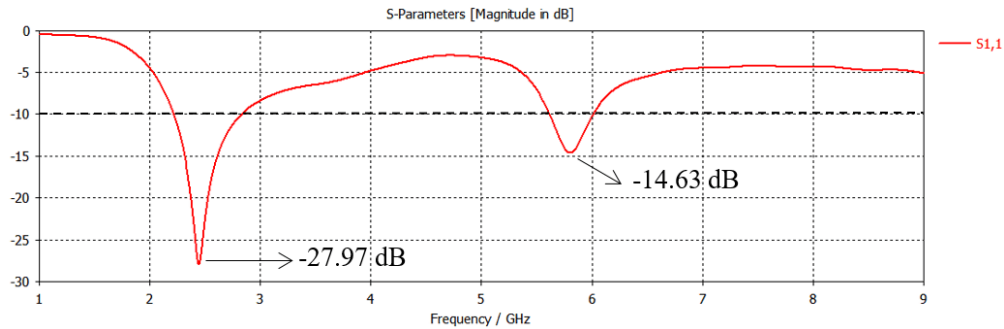


Figure 3.12: Simulated $S(1, 1)$ characteristics of proposed antenna.

3.5.6.2 VSWR

Figure 3.13 displays the plot of the voltage standing wave ratio as a function of frequency. The VSWR, or Voltage Standing Wave Ratio, is a metric used to quantify the degree of impedance mismatch between the feeding line and the antenna. An optimal VSWR value of 1 indicates perfect impedance matching, resulting in the acceptance of 100 percent power without any reflection. For optimal impedance matching, it is preferable to have a VSWR (Voltage Standing Wave Ratio) value below 2 in practical scenarios.

The antenna's voltage standing wave ratio is 1.083 at 2.45 GHz and 1.46 at 5.8 GHz, suggesting successful impedance matching at these resonant frequencies.

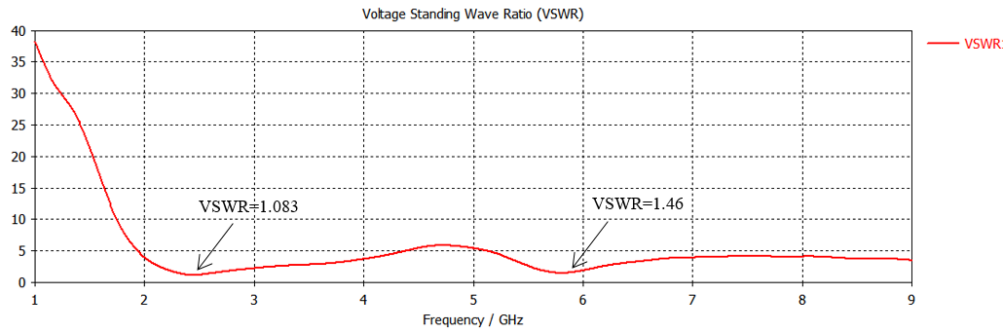
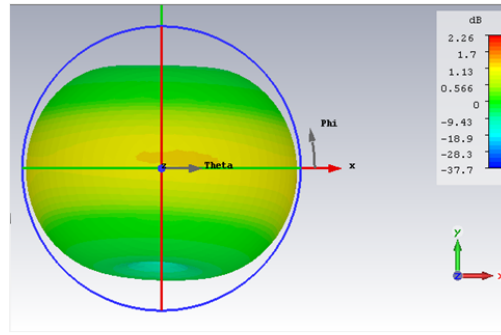


Figure 3.13: VSWR of the antenna

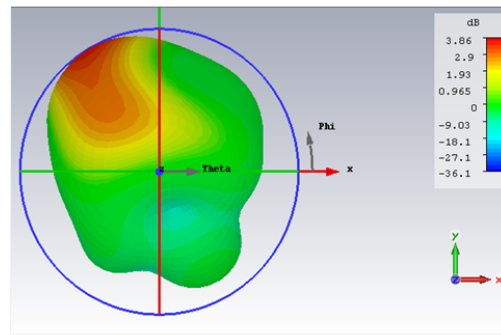
3.5.6.3 Gain and Directivity

Gain and directivity are crucial factors for evaluating the performance of an antenna. Figures 3.14(a) and 3.14(b) depict the three-dimensional gain patterns of the suggested antenna for frequencies of 2.45 GHz and 5.80 GHz, respectively.

Figures 3.15 (a) and 3.15 (b) show three-dimensional directivity plots that correspond to the same frequencies. The maximum gain values are 2.262 dB at a frequency of 2.45 GHz and 3.861 dB at a frequency of 5.84 GHz. At these frequencies, the directivity peaks are 2.6 dB and 5.2 dB, respectively.

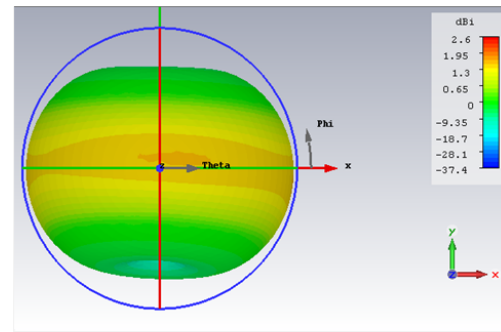


(a)

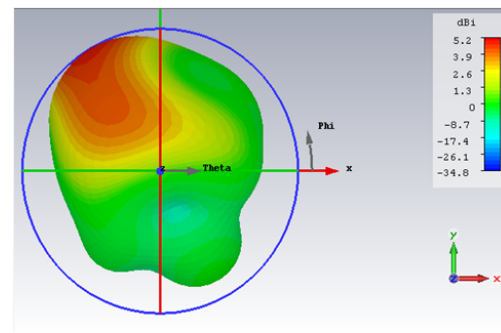


(b)

Figure 3.14: 3D gain plot of proposed antenna at (a) 2.45 GHz. (b) 5.8 GHz



(a)



(b)

Figure 3.15: 3D directivity plot of proposed antenna at (a) 2.45 GHz. (b) 5.8 GHz

The antenna under consideration has an efficiency of roughly 87% and at resonant frequency of 5.8 GHz, the efficiency is approximately 74%

Figure 3.16 illustrates the relationship between gain and frequency. The calculated antenna gain is determined to be 2.262 dB and 3.861 dB for the resonance frequencies of 2.45 GHz and 5.8 GHz, respectively. A 2.262 dB increase is generally moderate, but may be adequate for communication over short distances, such as within a hospital room or between body-worn sensors and a receiver in close proximity. Reducing the gain can also be beneficial in minimizing the possibility of interaction with other devices and ensuring safety. Medical devices must adhere to stringent standards and regulations. Using antennas with lower gain might decrease the specific absorption rate (SAR), thus ensuring the safety of the device for human use. A 3.861 dB increase at 5.8 GHz offers a slightly higher level of performance, which can be advantageous for applications that demand longer range or larger data rates.

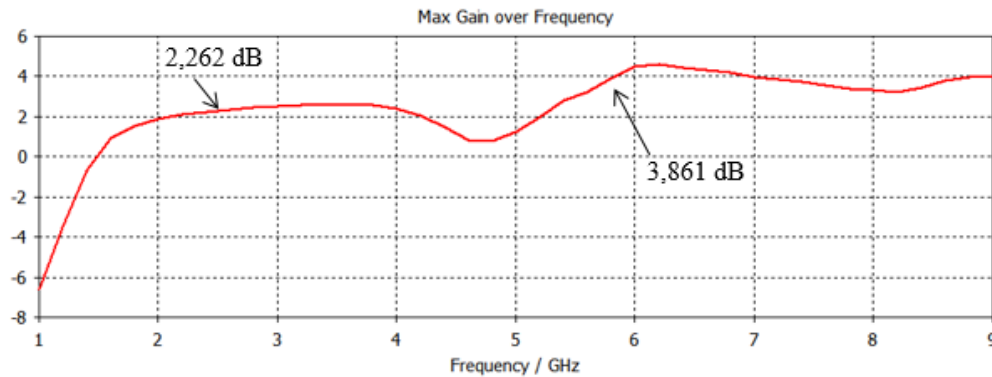


Figure 3.16: Peak gain of proposed antenna.

3.5.6.4 Current Distribution

The surface current distribution refers to the spatial arrangement of current density across a patch, indicating the variation of current density at different frequencies of operation. Figures 3.17 and 3.18 display the surface current distribution plots at specific resonance frequencies for our antenna. The analysis demonstrates that the highest current density is

achieved at the feed, indicating a significant coupling effect. The monopole antenna exhibits the lowest current density in its upper section. The current distribution on the monopole antenna confirms its favorable radiation characteristics and showcases enhanced performance in relation to the reflection coefficient and impedance matching.

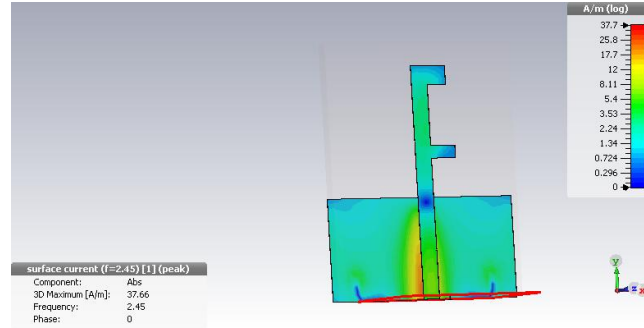


Figure 3.17: Surface current distribution for proposed antenna at 2.45 GHz.

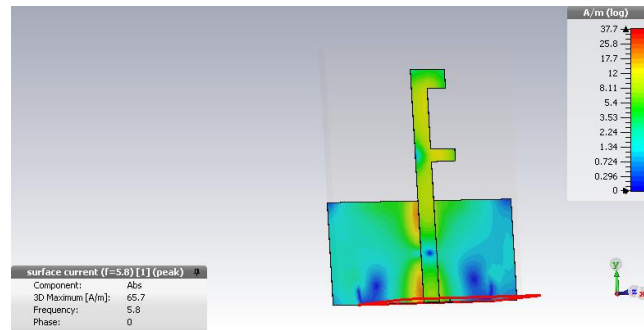
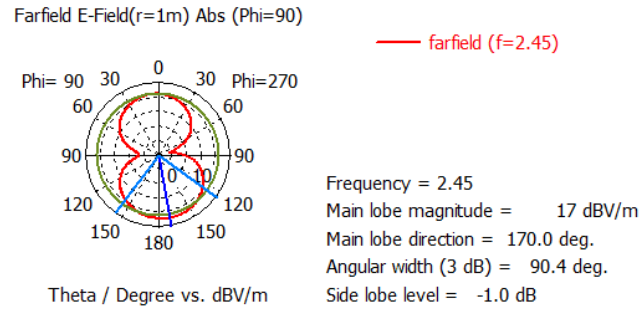


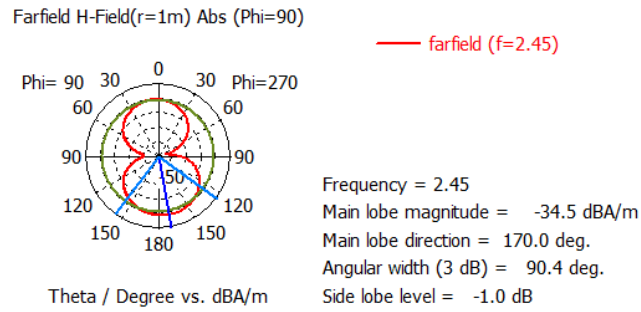
Figure 3.18: Surface current distribution for proposed antenna at 5.8 GHz

3.5.6.5 Radiation Pattern

The antenna radiation pattern is measured in the open air using the setup shown in Figures 3.19 and 3.20. The antenna is linearly polarized; therefore, its E- and H-plane patterns are analyzed to gain insight into its radiation characteristics in the two orthogonal planes. Pattern analysis reveals that the F-shaped antenna exhibits figure-of-eight radiation characteristics in the H (XZ) plane and produces a similar figure-of-eight pattern in the E (YZ) plane.

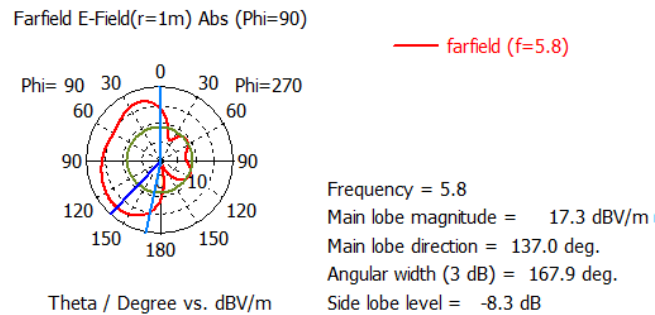


(a)

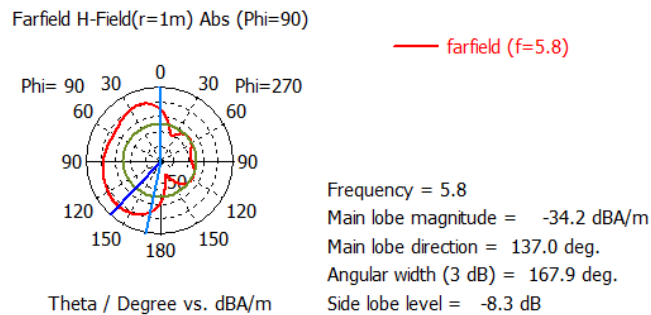


(b)

Figure 3.19: The E-plane and H-plane characteristics of the proposed antenna at 2.45 GHz.



(a)



(b)

Figure 3.20: The E-plane and H-plane characteristics of the proposed antenna at 5.8 GHz.

3.5.7 ANN Results

A dataset consisting of 121 samples was utilized to train the ANN models. For the Feedforward Backpropagation Neural Network (FFBPN), the architecture was configured with 2 neurons in the input layer, 10 neurons in the hidden layer, and 2 neurons in the output layer. The training function used was `trainlm`, and the learning rate was set to 0.15. For training the General Regression Neural Network (GRNN), a spread constant of 1 was selected. Figure 3.21 illustrates the performance plot of Mean Squared Error (MSE) versus the number of epochs. The best validation performance achieved was 3.9506×10^{-5} at epoch 21.

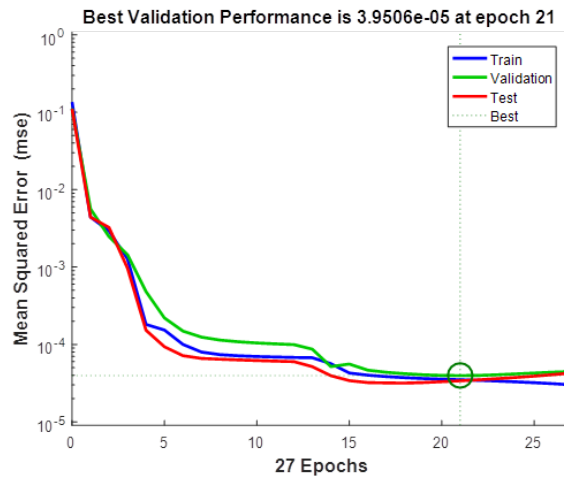


Figure 3.21: MSE Performance Over Epochs During Training

Tables 3.7 and 3.8 present the performance evaluation results of two different models using Mean Squared Error (MSE) and regression values across the training, validation, and testing phases for the General Regression Neural Network (GRNN) and Feedforward Backpropagation Neural Network (FFBPN), respectively.

Based on the evaluation results of both FFBPN and GRNN, it is observed that the FFBPN achieves the lowest Mean Squared Error (MSE) across all training, validation, and testing phases compared to GRNN. Since the primary objective of this work is the accurate prediction of resonant frequency values in antenna design, the accuracy of predicted values

is crucial, making MSE the most significant indicator in this context.

Although the regression coefficient (R) is slightly higher in the GRNN model, this metric only measures the linear relationship between actual and predicted outputs and does not always reflect the magnitude of the absolute error. Therefore, considering the need for precise frequency prediction in antenna applications, where even small deviations are critical, the FFBN model is more suitable due to its superior accuracy in absolute value predictions, as confirmed by the plotted results and absolute error comparisons.

Table 3.7: Performance results in terms of MSE and regression for GRNN

Phase	MSE	Regression
Train	0.0089717	0.99557
Validation	0.0094297	0.99901
Test	0.0085885	0.85399

Table 3.8: Performance results in terms of MSE and regression for FFBN

Phase	MSE	Regression
Train	2.5038×10^{-5}	0.99393
Validation	3.0653×10^{-5}	0.96992
Test	8.6203×10^{-5}	0.84270

The performance of two distinct artificial neural networks (ANNs) was assessed using the same dataset. Tables 3.9 and 3.10 illustrate the comparison between FFBN and GRNN outputs against the desired outputs based on absolute error. Additionally, Table 3.11 provides a comparison of the average absolute errors for both ANNs with respect to f_{r1} and f_{r2} . The results indicate that FFBN consistently exhibits lower average absolute errors compared to GRNN for both f_{r1} and f_{r2} . Consequently, FFBN is favored over GRNN for this study.

Table 3.9: Comparison of Desired and FFBN Outputs with Errors

L2	L3	Desired f1	Desired f2	FFBN f1	FFBN f2	Abs. Error1	Abs. Error2
3.5	4.8	2.448	5.728	2.4469	5.7299	0.0010575	0.0018825
4.1	4.2	2.416	5.912	2.4134	5.8983	0.0026017	0.013716
3.9	3.6	2.424	6.112	2.4228	6.1159	0.0011639	0.0038604
2.7	5.0	2.488	5.712	2.4894	5.7049	0.0013718	0.0070951
2.9	3.8	2.480	6.144	2.4814	6.1390	0.0013789	0.0050485
3.3	4.8	2.456	5.774	2.4578	5.7510	0.0018402	0.022974
3.5	4.0	2.448	6.016	2.4448	6.0221	0.0032136	0.0060647
2.5	4.0	2.496	6.112	2.4995	6.1165	0.0034875	0.0045105
3.3	4.4	2.456	5.896	2.4561	5.8908	0.0000626	0.0052446
3.1	3.2	2.472	6.344	2.4687	6.3356	0.0033413	0.0084424

Table 3.10: Comparison of Desired and GRNN Outputs with Errors

L2	L3	Desired f1	Desired f2	GRNN f1	GRNN f2	Abs. Error1	Abs. Error2
3.5	4.8	2.448	5.728	2.4464	5.8966	0.0016241	0.16857
4.1	4.2	2.416	5.912	2.4326	5.9594	0.0166010	0.047429
3.9	3.6	2.424	6.112	2.4372	6.0569	0.0131600	0.055131
2.7	5.0	2.488	5.712	2.4642	5.9001	0.0238080	0.18809
2.9	3.8	2.480	6.144	2.4605	6.0686	0.0195270	0.075398
3.8	4.8	2.456	5.774	2.4511	5.9042	0.0048849	0.13023
3.5	4.0	2.448	6.016	2.4465	6.0136	0.0015037	0.0023561
2.5	4.0	2.496	6.112	2.4683	6.0514	0.0276580	0.060625
3.3	4.4	2.456	5.896	2.4512	5.9607	0.0048282	0.064692
3.1	3.2	2.472	6.344	2.4563	6.1455	0.0157270	0.19847

Table 3.11: Average Absolute Errors for Different Networks

Network	Avg Abs Error f1	Avg Abs Error f2
FFBN	0.002292	0.0056708
GRNN	0.017468	0.1128900

Figures 3.22 and 3.23 present graphical comparisons of FFBN and GRNN outputs against the desired outputs for f_{r1} and f_{r2} , respectively. Figure 3.24 depicts a comparative analysis of the errors for both ANNs as a function of the number of samples.

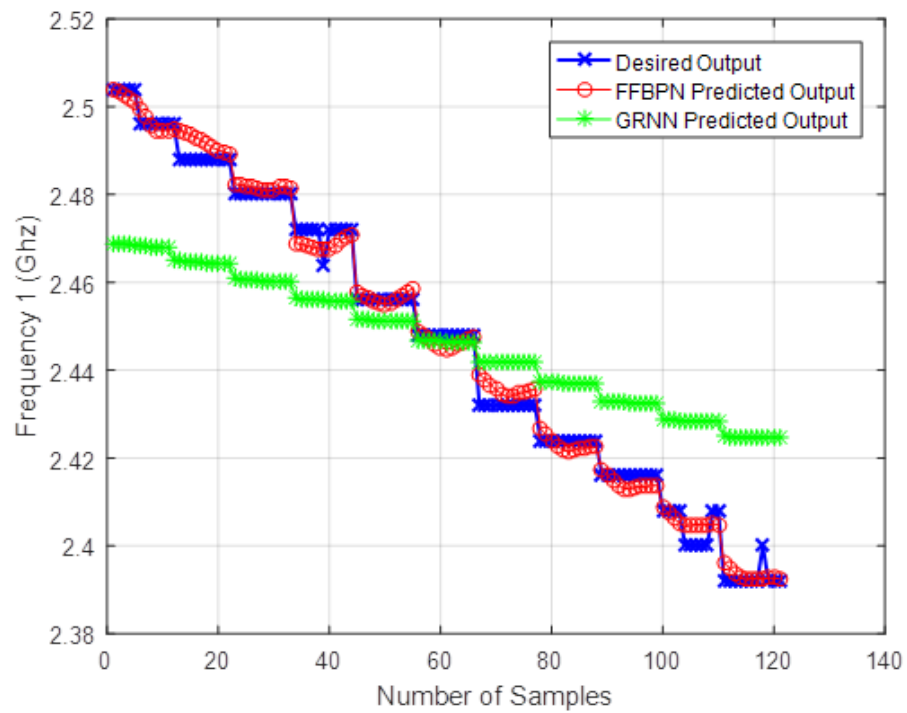


Figure 3.22: Comparison of ANN Outputs with Desired Output for Frequency 1

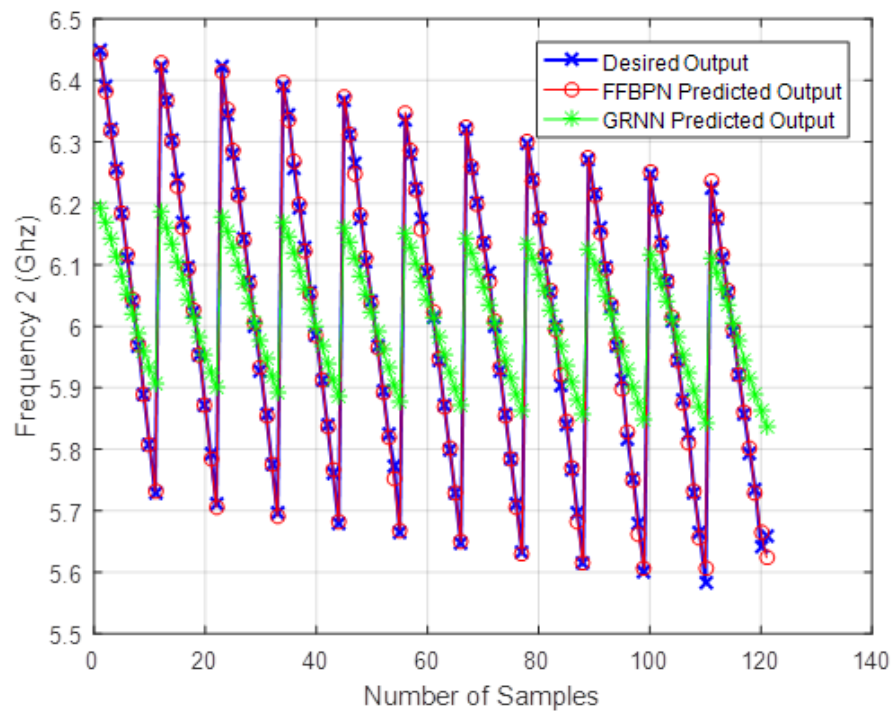


Figure 3.23: Comparison of ANN Outputs with Desired Output for Frequency 2

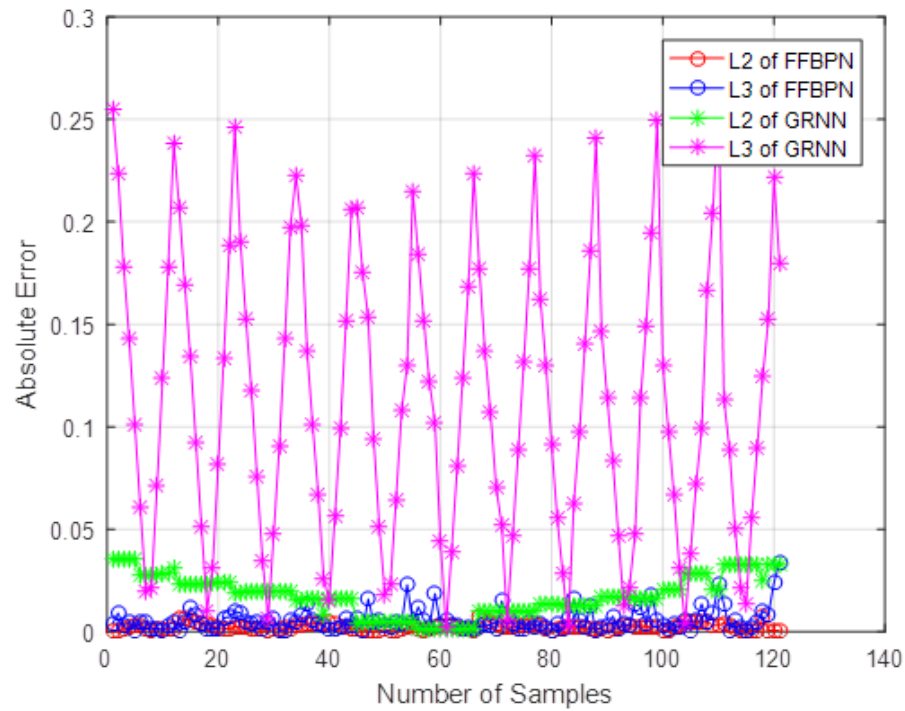


Figure 3.24: Comparison of Errors of Both ANNs versus Number of Samples

Figures 3.25 and 3.26 illustrate the comparison between real and predicted resonant frequencies for the dual-band antenna using both FFBN and GRNN models. It can be observed that the FFBN predictions exhibit closer alignment with the ideal line for both frequency bands, indicating higher prediction accuracy compared to the GRNN model.

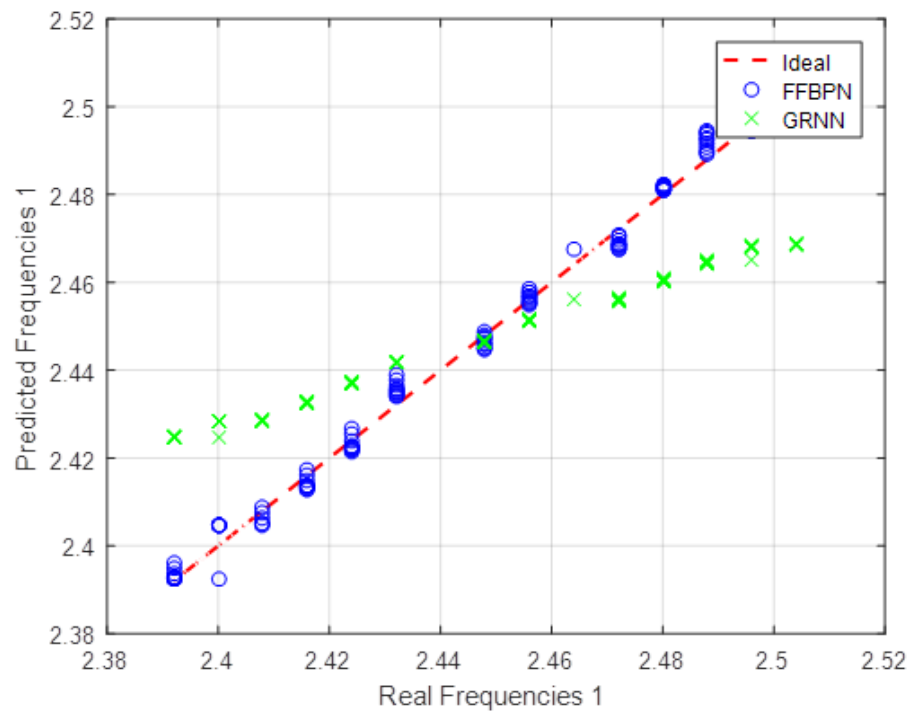


Figure 3.25: Predicted Frequencies 1 vs. Real Frequencies 1

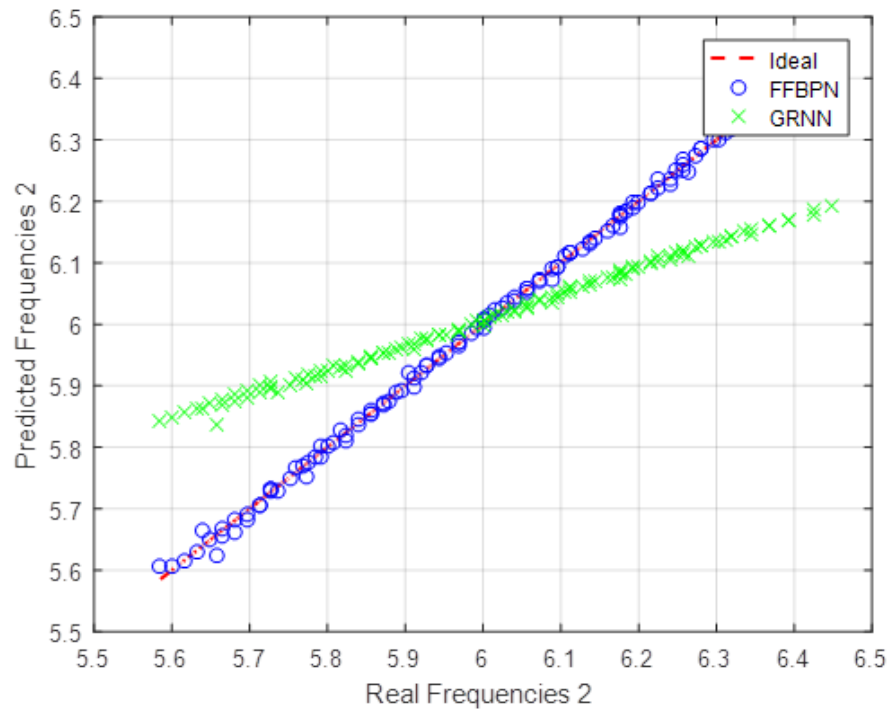


Figure 3.26: Predicted Frequencies 2 vs. Real Frequencies 2

3.5.7.1 PSO Results

The objective of particle swarm optimization (PSO) is to optimize the parameter values L_2 and L_3 to achieve the desired resonance frequencies (fr1 and fr2). The algorithm starts with a cohort of 40 particles and a cap of 1000 iterations. The design parameter is established within suitable minimum and maximum limits, creating a two-dimensional area for optimization. PSO subsequently explores the optimal parameter values of the proposed planned antenna. The cost function has been used to establish that the optimal parameter values L_2 is 3.5mm. The optimal parameter values L_3 are 4.6mm.

3.5.7.2 ANTENNA PROTOTYPE

The fabricated antenna is shown in Figure 3.27. It is printed on an FR4 substrate and features an F-shaped radiating structure. This geometry is specifically designed to support dual-band operation at 2.45 GHz and 5.8 GHz.

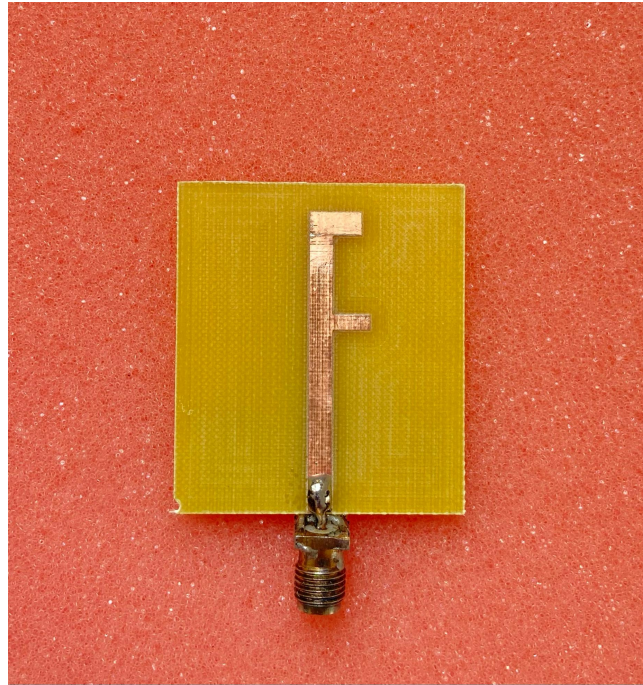


Figure 3.27: Top view of the fabricated F-shaped microstrip antenna.

Figure 3.28 illustrates the measurement setup used to evaluate the return loss (S_{11}) per-

formance of the antenna. The device is connected to a Vector Network Analyzer (Agilent PNA-L) through a coaxial cable. To reduce unwanted reflections and external interference, the antenna is placed on a pyramidal RF absorbing foam during measurement.

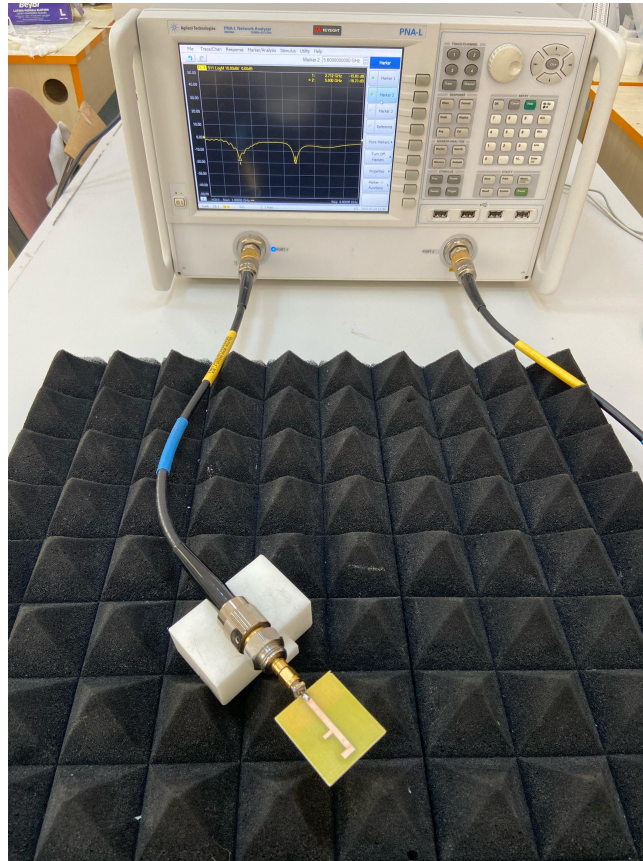


Figure 3.28: Measurement setup using a Vector Network Analyzer (VNA).

The comparison between simulated and measured return loss results is presented in Figure 3.29. A good agreement is observed between the two curves, with resonances appearing around 2.45 GHz and 5.8 GHz in both cases. Slight discrepancies in the return loss levels can be attributed to fabrication tolerances and connector losses, which are common in practical implementations.

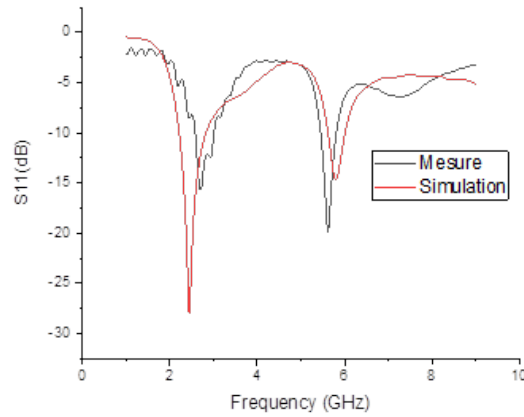


Figure 3.29: Comparison of simulated and measured S_{11} results.

Throughout the different stages of this research, a sequential and progressive development approach has been adopted. Initially, single-objective optimization was considered, focusing on specific antenna characteristics such as S_{11} . As the work evolved, the need to address more complex biomedical requirements became evident, particularly the simultaneous consideration of multiple performance metrics such as gain S_{11} and Specific Absorption Rate (SAR). This led to the adoption of multi-objective optimization strategies, allowing for a comprehensive evaluation of antenna designs. The transition from single- to multi-objective optimization reflects the natural progression of the research, aligning with the increasing complexity of biomedical and other advanced applications. A detailed implementation of this multiobjective optimization approach will be presented in Chapter 4.

3.6 Conclusion

This chapter provided a detailed exploration of Artificial Neural Networks and their role in antenna design. After introducing the fundamental principles of ANN operation and evaluating the performance of different learning algorithms, the chapter presented several case studies that demonstrated the effectiveness of ANN-based optimization.

The results confirmed that ANNs can accurately predict antenna parameters such as resonant frequencies, return loss, gain, and radiation patterns. Comparisons between ANN predictions, electromagnetic simulations, and experimental measurements showed strong agreement, validating the reliability of the models.

Overall, the chapter demonstrated that ANN-assisted approaches offer significant advantages in terms of accuracy, computational efficiency, and adaptability. These findings establish a solid foundation for the next chapter, which introduces multi-objective inverse neural network models for advanced biomedical antenna optimization.

Chapter 4

Inverse Neural Networks for Multi-Objective Biomedical Antenna Design

4.1 Introduction

While the previous chapter demonstrated the potential of Artificial Neural Networks (ANNs) for predicting antenna performance, this chapter advances the concept by introducing inverse neural network models for multi-objective optimization. Unlike conventional forward models, which predict antenna characteristics from given design parameters, inverse models work in the opposite direction—identifying suitable geometrical parameters based on desired performance goals.

The chapter first introduces three different inverse ANN models, including the proposed approach that enhances prediction accuracy and generalization capability. Data preparation and dataset splitting strategies are also discussed to ensure robust training and validation.

Application examples are then presented, focusing on biomedical antenna design under various conditions. These include evaluating the reflection coefficient, gain, and Specific Absorption Rate (SAR) in free space, within tissue, and using tissue inverse models. Compar-

isons between HFSS simulations and ANN predictions are provided to assess model accuracy. Finally, the chapter concludes with the fabrication and measurement of a prototype antenna, validating the practical feasibility of the proposed optimization methodology.

4.2 ANN Model

The ANN models developed in this section are based on the same methodology applied in Sections 3.3.2 and 3.5.3, where the Levenberg-Marquardt (LM) algorithm was employed for training. The main difference, however, lies in the input features used. Here, the models are built using only the reflection coefficient S_{11} , the gain, and the SAR parameter in the presence of a phantom, which provides a more realistic evaluation of antenna performance in biomedical scenarios.

The first and second models are thus constructed with this input configuration, with slight differences between them that will be discussed in detail in Sections 4.2.1 and 4.2.2. Finally, the proposed third model (Section 4.2.3) extends this methodology by adopting a multi-objective inverse ANN approach, enabling simultaneous optimization of multiple performance metrics and providing a more comprehensive design framework.

4.2.1 The first model

In this study, an artificial neural network model is developed to predict the geometrical parameters of a microstrip antenna based on simulation data. The ANN model consists of three independent neural networks, each designed to process different input features. As shown in Figure 4.1, the first ANN receives 101 values of S_{11} , simulating the 101 frequency steps spreading from 0.6 GHz to 10.6 GHz with a step of 0.1 GHz as inputs and predicting six geometrical parameters as outputs. The second ANN is trained on gain-related parameters for the same number and nature of inputs and outputs, while the third ANN utilizes SAR

values as input. Each ANN model consists of two hidden layers of five neurons in each one. A MATLAB program was developed to implement the model, integrating nine different optimization algorithms. The simulation-based generated data set is partitioned as follows: 70% for training, 15% for validation, and 15% for testing. Performance evaluation is conducted using mean squared error (MSE) metrics to assess prediction accuracy. After training, each ANN is tested on an independent data set, here, new S11, gain, and SAR values are fed into their respective networks to predict antenna geometrical parameters.

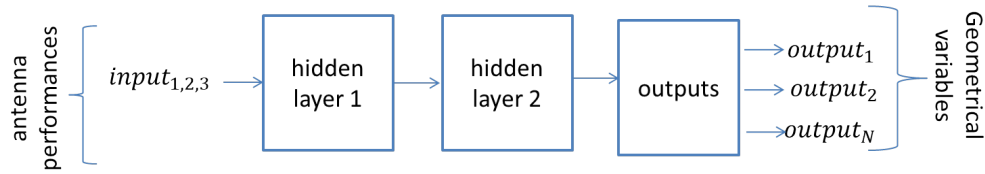


Figure 4.1: Inverse Artificial Neural Network with separate inputs.

4.2.2 The second model

In the second model, the 101 values of the S11 parameter, gain, and SAR corresponding to each frequency step are used as inputs simultaneously for a single ANN model as shown in Figure 4.2. The ANN architecture includes (3×101) inputs, two hidden layers with five neurons in each layer to predict the six geometrical parameters or outputs of the considered design. Model performance is assessed through statistical error metrics, particularly RMSE, ensuring high accuracy and reliability for antenna design optimization.

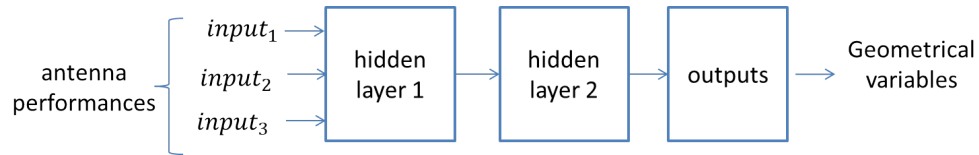


Figure 4.2: Inverse Artificial Neural Network with Non-separated inputs.

4.2.3 The third model (Proposed model)

The proposed model is a partially connected neural network, it consists of two parts. The first part consists of three branches. The second part consists of one fusion layer, as illustrated in Figure 4.3.

Part I: Three Parallel Branches

Branch 1 (S₁₁ Features Processing): This branch establishes the local connection between the S_{11} parameters and the geometrical parameters of the design.

- **Input Layer:** The inputs of this layer consist of the S_{11} parameters extracted from the dataset.
- **Locally Connected Layer 1:** Applies independent feature extraction operations on S_{11} values without shared weights. Five neurons are used in this layer.
- **Activation Layer 1:** Applies a nonlinear activation function, in this case study, we used the sigmoid activation function.

Branch 2 (Gain Features Processing): This branch establishes the local connection between the antenna maximum gain and the geometrical parameters of the design.

- **Input Layer:** The inputs of this layer consist of the maximum gain extracted from the dataset.
- **Locally Connected Layer 1:** Applies independent feature extraction operations on the gain values without shared weights. Five neurons are used in this layer.
- **Activation Layer 1:** Applies a nonlinear activation function, in this case study, we used the sigmoid activation function.

Branch 3 (SAR Features Processing): This branch establishes the local connection between the Specific Absorption Rate (SAR) and the geometrical parameters of the design.

- **Input Layer:** The inputs of this layer consist of the SAR extracted from the dataset.
- **Locally Connected Layer 1:** Applies independent feature extraction operations on SAR values without shared weights. Five neurons are used in this layer.
- **Activation Layer 1:** Applies a nonlinear activation function, in this case study, we used the sigmoid activation function.

Part II: Fusion Layer and Fully Connected Network

- **Fusion Layer:** Combines outputs from all three branches, aggregating information from S_{11} , gain, and SAR data.
- **Fully Connected Layers:** A sequence of dense layers with a hidden structure of [5,5,5,5], optimizing the extracted features.
- **Output Layer:** Predicts the desired parameters that correspond to the optimized antenna geometrical parameters.

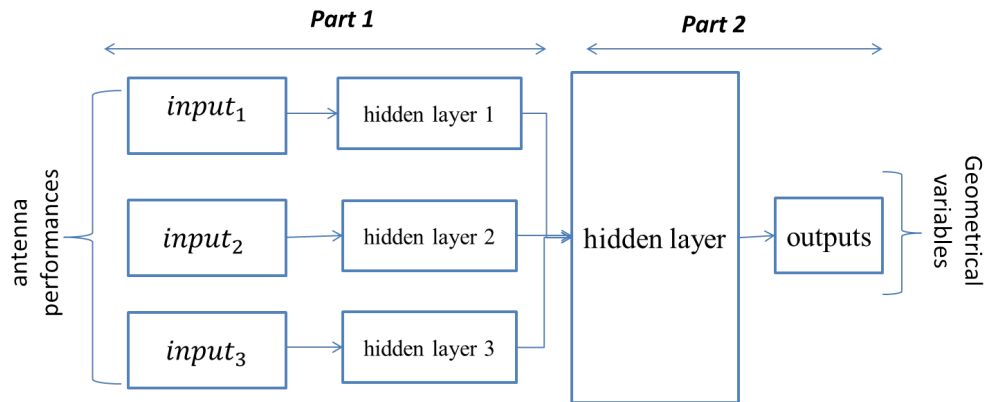


Figure 4.3: The proposed Inverse Neural Networks.

The proposed inverse model comprises five distinct layers. The initial segment encompasses an input layer containing three independent blocks corresponding to S-parameters, independent gain values, and SAR. Following this, the first hidden layer and the first output layer are strategically employed to establish a mapping between the three performance indices and the associated geometrical variables. The subsequent segment of the model encompasses the Fourth and Fifth layers: a Second Hidden layer and a Second Output layer, which collectively culminate in the generation of the final predicted result. The hyperbolic sigmoid function is the activation function that is employed in the three layers. Nonlinearity has been included in these branches to enable the network to learn. The proposed model is flexible and can be adapted to include other performance metrics, such as radiation pattern, efficiency, or directivity, if required by specific design constraints.

4.2.4 Splitting a dataset

The data set consists of three matrices with 256 samples for each, divided into three distinct cases: free space, tissue, and tissue inverse. Each case is further divided into training, validation, and testing subsets according to a specified ratio. Specifically, 70% of the data is allocated to the training set, 15% to the validation set, and 15% to the testing set. This splitting ratio ensures that a significant portion of the data set is dedicated to training, which is crucial for the neural network to learn effectively. The effectiveness of the neural network model developed is closely dependent on this data allocation. The performance of the model is defined by the relative mean square error. where the relative mean square error (RMSE) can be interpreted as follows: less than 10% indicates excellent accuracy, between 10% and 20% indicates good accuracy, between 20% and 30% indicates fair accuracy, and greater than or equal to 30% indicates poor accuracy.

4.3 Application examples

To demonstrate the effectiveness of the three neural models described in the previous section, a rectangular patch microstrip antenna is used [146]. The proposed antenna uses an FR-4 substrate with a thickness of 1.58 mm and a relative dielectric permittivity of 4.4, A trapped $50\ \Omega$ microstrip line is used to feed it. This type of antenna, characterized by its compact size, design flexibility, cost-effectiveness, and ability to integrate with other components, makes it an excellent choice for various applications, including biomedical ones. Simulations were carried out using HFSS software,

The antenna size parameters are summarized in Table 4.1. Six geometrical parameters were used to generate the dataset. The obtained values of S_{11} , gain, and SAR are recorded to form the desired antenna performances. The inverse modeling using a neural network model consists of exchanging the inputs with the outputs so as to establish the relationship between the desired performances taken as inputs and the corresponding geometrical parameters taken as outputs. In this case study, the six geometrical parameters predicted by the proposed neural models are $t = [df, ex1, ex2, xpf1, xpf2, Lg]$, these parameters are illustrated in Figure 4.4. The minimum and maximum values as well as the incremental step are given in Table 4.2.

Table 4.1: Antenna size parameter

Paramater	dimension
W	13
L	12
Yf	12.5
Wsub	20
Lsub	24
H	1.58
T	0.035

Table 4.2: Training data of geometrical variables in (mm)

geometrical variables	min	max	step
df	-2	2	4
ex1	0.5	3.5	1
ex2	1.5	4.5	1
xpf1	13.5	16	2.5
xpf2	10	14	4
Lg	5	15	10

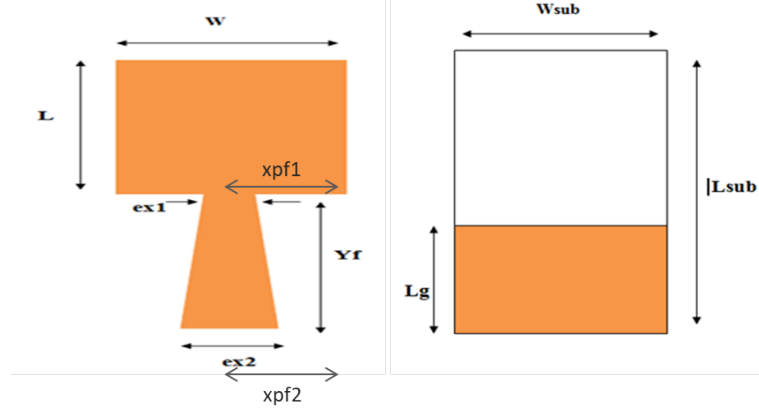


Figure 4.4: The proposed antenna's front and back views in HFSS.

In this study, three cases are considered: in the first case, the antenna is placed in free space, in the second, it is placed on top of a model made up of three layers imitating the human body in this case, the ground plane facing the ghost. In the third case, the antenna is inverted, and it is the patch that faces the human model.

Figure 4.5 illustrates the phantom model, it consists of three distinct layers representing the skin, the fat, and the muscle.

The dielectric properties of the human tissues used in this study are given in table 4.3 they were taken from [147]. However, for more accurate SAR evaluation, these properties can be experimentally measured using different techniques such as the open-ended coaxial probe method, as demonstrated in [148].



Figure 4.5: Representation of a human tissues model.

Table 4.3: Material properties of the human body

	Skin	Fat	Muscle
Conductivity(s/m)	3.0608	0.24222	4.0448
Relative permittivity	35.7	5.0291	49.54
Loss tangent	0.3076	0.17315	0.29353

4.4 Results and discussions

To show the close relationship between antenna performances with these geometric parameters, a parametric study was conducted over a wide frequency range by varying key design parameters, such as feed width, feed position, ground plane length, and feed line displacement from center. The results, illustrated in Figure 4.6, demonstrate how these parameters affect the impedance matching of the antenna, the operating frequency band, and the frequency bandwidth. The resulting data were then incorporated into the artificial neural network (ANN) training dataset to enable accurate performance prediction and optimization. This approach ensures that the ANN effectively captures the relationship between geometric variations and antenna characteristics, thereby facilitating the efficient design of antennas for biomedical applications.

The study utilized three different ANN models: the first model, the second model, and the proposed model. Each model was tested under three conditions: in free space, with tissue,

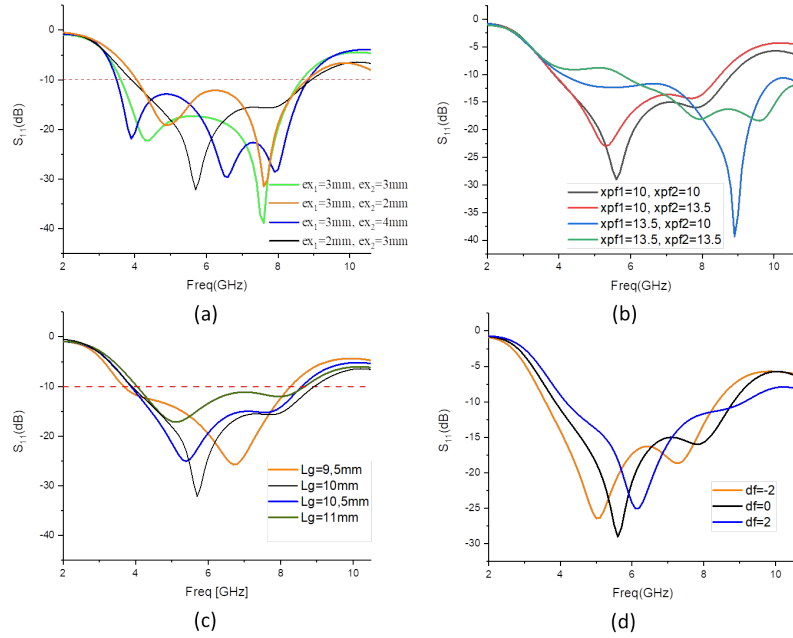


Figure 4.6: Parametric Analysis of Antenna Performance: (a) Effect of Feed Width, (b) Effect of Feed Position, (c) Effect of Ground Plane Length, (d) Effect of feed line displacement from the center.

and with tissue inverse. The parameters of interest included the reflection coefficient S_{11} , gain, and Specific Absorption Rate (SAR). The geometrical variables were obtained through training and were used to create antenna structures. The synthesis consists of inputs the reflection coefficient S_{11} to get the geometrical dimensions $[df, ex1, ex2, xpf1, xpf2, Lg]$. Our objective was to evaluate each suggested model's performance compared with the others, which are $[0, 2, 3, 10, 10, 10]$. These geometrical variables obtained are not included in the training set.

4.4.1 Results obtained in free space

Figure 4.7 presents the reflection coefficient (S_{11}) results obtained from simulations using HFSS and predictions from three different models of ANN: the first model, the second model, and the proposed model, in a free-space environment. The graph clearly shows how the proposed ANN model (green line) aligns closely with the HFSS simulated results (black line)

across the frequency range of 0.6 to 10.6 GHz, indicating improved accuracy and reliability over the first model (red line) and second models (blue line). The proposed model's ability to maintain low reflection coefficients at key frequencies demonstrates its effectiveness in optimizing antenna design, particularly around the resonant frequencies where minimal reflection is desired.

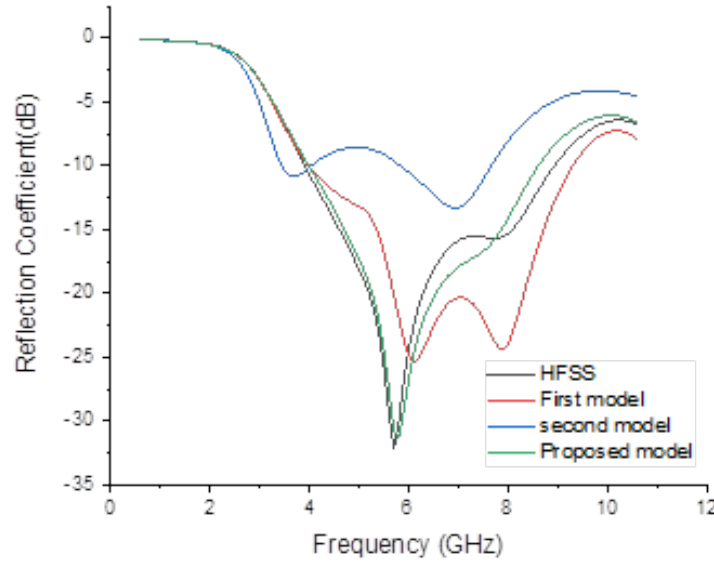


Figure 4.7: Results of reflection coefficient obtained using HFSS and ANN models in free space.

Figure 4.8 illustrates the gain results achieved using HFSS simulations compared to the predictions made by three ANN models: the first model, the second model, and the proposed model, in free space. The proposed ANN model (green line) shows a gain pattern that closely follows the HFSS results (black line) in the entire frequency band, showcasing its enhanced predictive capability. The proposed model's improved gain predictions over the entire frequency spectrum, especially around the resonance points, highlight its efficiency in antenna design optimization. This enhanced gain consistency across different frequencies reflects the proposed model's superior performance compared to the first (red line) and second

models (blue line).

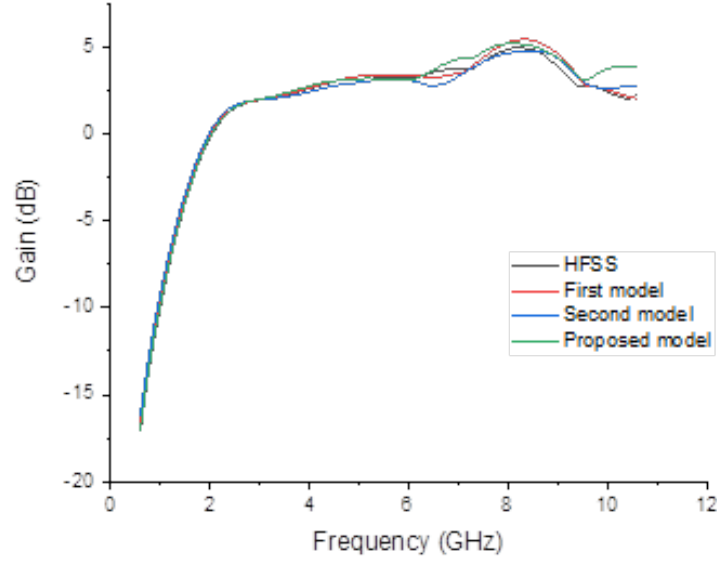


Figure 4.8: Results of Gain obtained using HFSS and ANN models in free space.

4.4.2 Results obtained with tissue

The introduction of the phantom causes a frequency shift towards the low frequencies, as illustrated by figure 4.9. As the frequency band in this study is fixed for all generated data (ranging from 0.6 GHz to 10.6 GHz with a step of 0.1 GHz), the frequency shifting manifests with S11 that does not start from 0 dB but at a lower value that is not taken into account in the considered frequency band. The effectiveness of the proposed neuronal model is more apparent in the case with tissue, in fact as shown in the results of Figure 4.9 a narrow band behavior is achieved in the case of the first and second models with a peak around 1 GHz. While the results obtained with the proposed neural model follow the pattern of those obtained with HFSS with a wider bandwidth for the proposed model

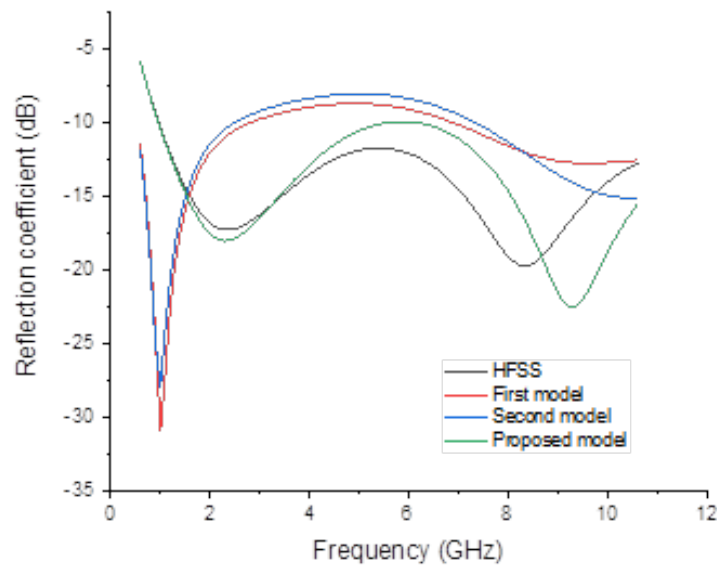


Figure 4.9: Results of reflection coefficient obtained using HFSS and ANN models with tissue

Figure 4.10, depicting gain versus frequency, demonstrates that the proposed ANN model aligns closely with the HFSS software, achieving consistent and high gain values across the frequency range, the same observation for the first model. In contrast, the second ANN model exhibits significant deviations, particularly at frequencies above 6 GHz.

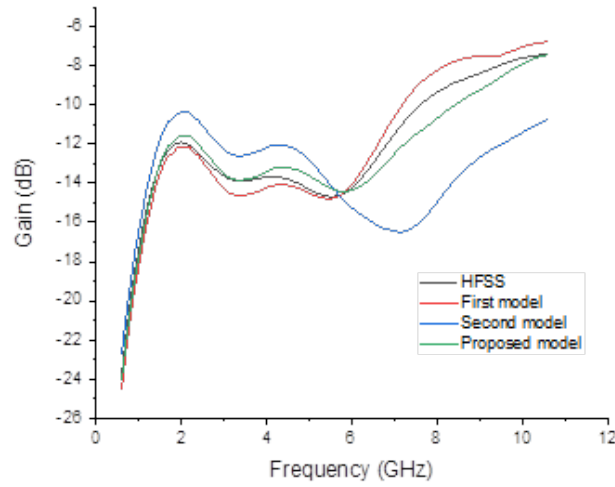


Figure 4.10: Results of Gain obtained using HFSS and ANN models with tissue .

Figure 4.11 shows SAR versus frequency, where lower values are crucial for safe biomedical applications. The proposed ANN model again excels, closely matching the HFSS SAR values and indicating safer energy absorption levels. The first ANN model shows significantly higher SAR values, and while the second ANN model is improved, it still exceeds the benchmark. Overall, the proposed ANN model consistently shows the best performance across all

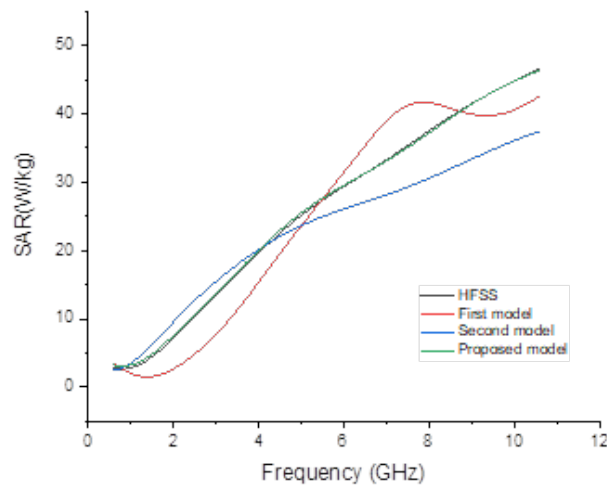


Figure 4.11: Results of SAR obtained using HFSS and ANN models with tissue .

parameters, making it the most optimized and suitable choice for biomedical applications among the evaluated models. Overall, the proposed ANN model consistently shows the best performance across all parameters, making it the most optimized and suitable choice for biomedical applications among the evaluated models.

4.4.3 Results obtained with tissue inverse

In Figure 4.12, which shows the reflection coefficient versus frequency, the proposed model closely matches the HFSS results, especially at lower frequencies (below 4 GHz). There are minor deviations between the models, particularly between 4 GHz and 8 GHz, but all models exhibit similar trends, indicating that the proposed model is a good approximation of the HFSS results. The term “with tissue inverse” indicates that the antenna was inverted so that its radiating surface faces away from the tissue, thereby reducing the electromagnetic coupling and minimizing the energy absorbed within the human body.

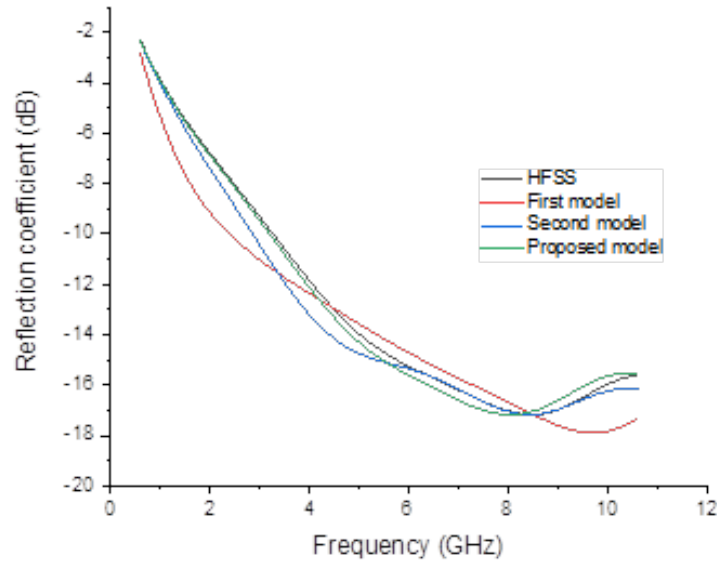


Figure 4.12: Results of reflection coefficient obtained using HFSS and ANN models with tissue inverse .

In Figure 4.13, which presents gain versus frequency, the gain values of the proposed model are quite close to the HFSS results over the entire frequency range. The second model also presents results very comparable to those of the HFSS, the greatest deviation is recorded by the first model, especially for high frequencies.

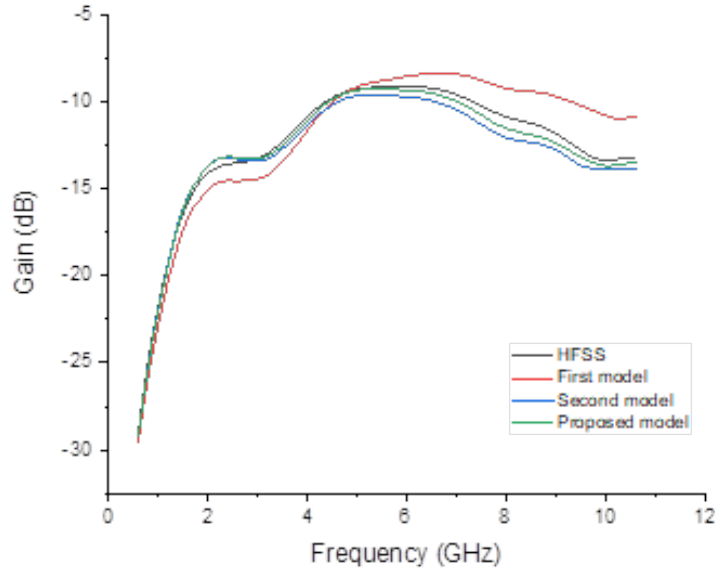


Figure 4.13: Results of Gain obtained using HFSS and ANN models with tissue inverse.

The results obtained for the SAR, Figure 4.14, confirm these. obtained for the two previous performances, namely the S11 and the gain. Indeed, once again, the results obtained by the proposed model closely follows those of HFSS followed by those of the second model, while the first model records the largest deviation.

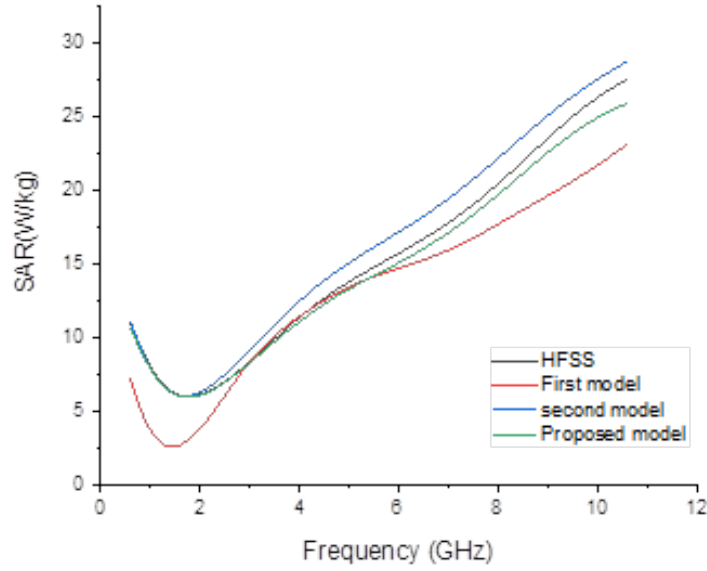


Figure 4.14: Results of SAR obtained using HFSS and ANN models with tissue inverse.

According to the results illustrated in Figure 4.15, the SAR value measured at the 5.8 GHz frequency is 28.7799 W/kg for the with tissue case and 15.5273 W/kg for the with tissue inverse case, and it increases with frequency. To mitigate the SAR, it can be effectively controlled by reducing the input power delivered to the antenna. The formula for calculating the SAR has already been presented in Section 1.3.4. Based on this formulation, the estimated input power corresponding to a SAR of 28 W/kg at 5.8 GHz, considering a hand mass of approximately 0.0412 kg, is about 1153.6 mW for the with tissue case and 639.7 mW for the with tissue inverse case.

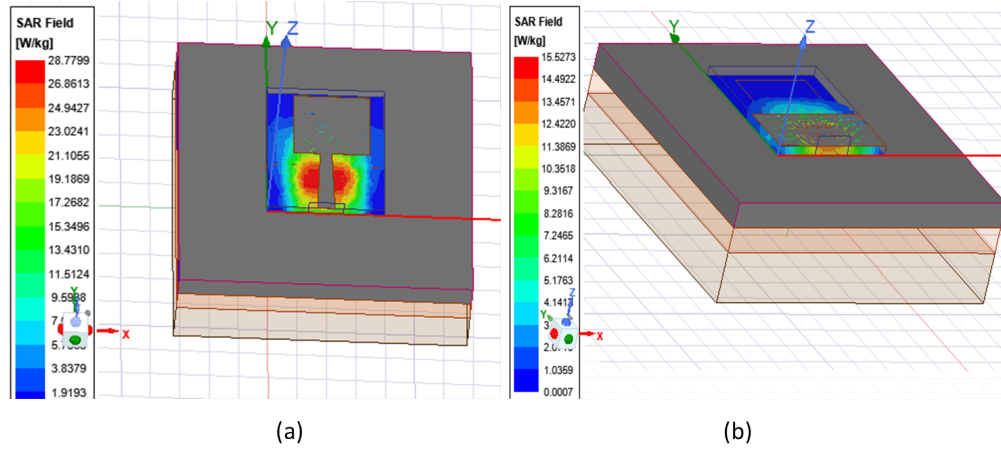


Figure 4.15: Results of SAR average in frequency 5.8 obtained using HFSS (a) with tissue (b) with tissue inverse.

To show the performance of the designed antenna in terms of radiation, the E plan and the H plan radiation patterns were plotted for the frequencies 3.6 GHz, 5.8 GHz, and 8.3 GHz covering the entire frequency range and for the three cases studied, namely free space, on the tissue, and on the tissue inverse. These diagrams illustrated in Figure 4.16 are obtained by HFSS simulation and not by neural models. A quasi-omnidirectional radiation pattern is obtained in both planes. A slight increase in gain can be seen in the case with tissue and with tissue inverse because of the reflection at the air/skin interface. Stability of the diagrams over the entire frequency range was also observed.

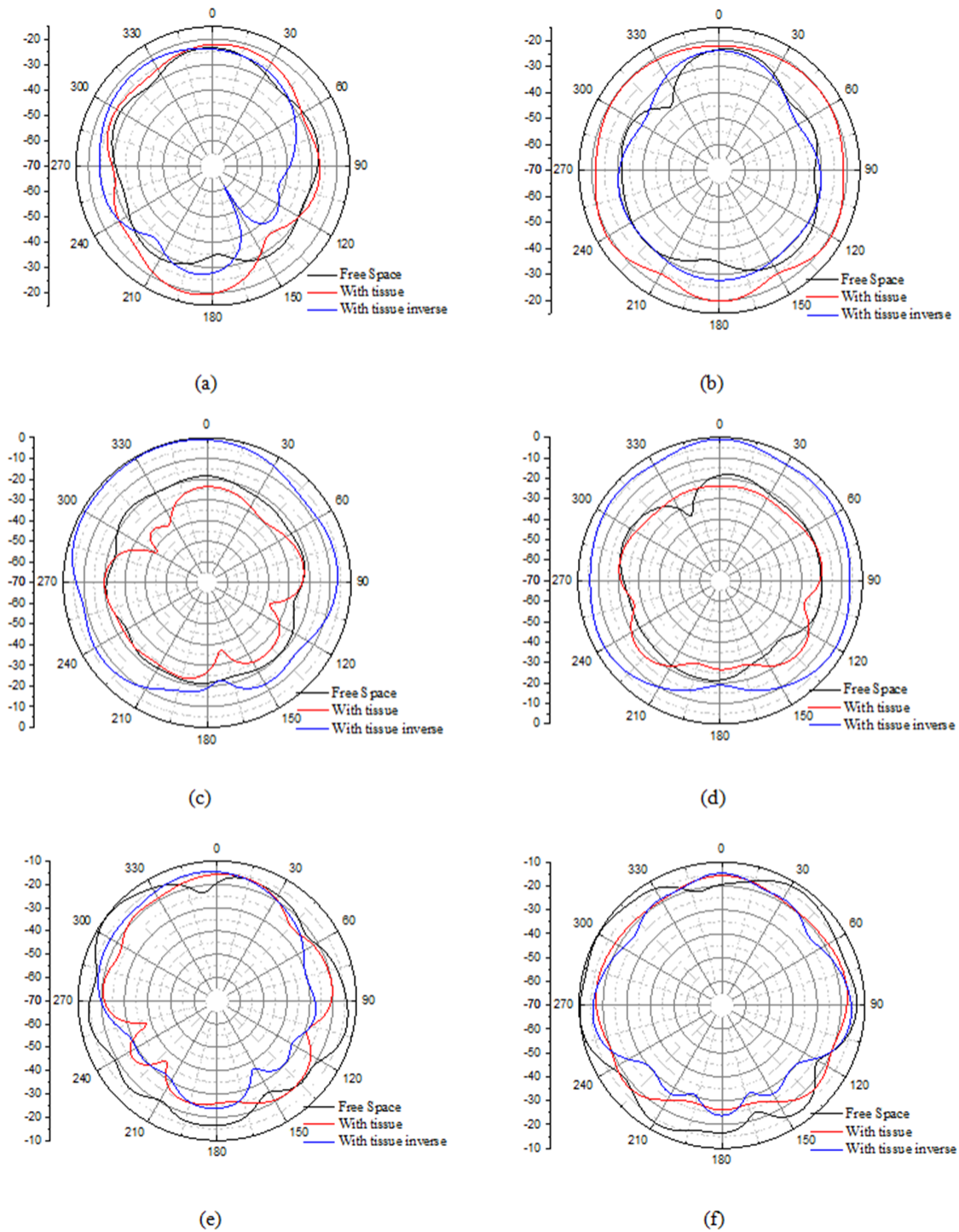


Figure 4.16: Radiation pattern of the first antenna structure according to the three possibilities for the frequencies 3.6 GHz ((a) E-plane, (b) H-plane), 5.8 GHz ((c) plan E, (d) plan H) and 8.3 GHz ((e) plan E, (f) plan H).

The results reported in Tables 4.4, 4.5 and 4.6 highlight the performance of three neural models in predicting geometric variables under various conditions. The maximum value of the RMSE recorded by the first model is 2.4885 (SAR as inputs) in the case of tissue and its minimum value is 0.3104 (gain as inputs) recorded in the case of free space (table 4.4). The second neural modal recorded a maximum RMSE of 1.9107 (S11, gain and SAR as inputs) in the case with tissue and a minimum value of 0.3281 in the case with inverse tissue (table 4.5). The proposed modal recorded a maximum RMSE of 0.4314 in the case with tissue and a minimum RMSE of 0.0979 obtained in the case of free space. These results confirm that the proposed model is very effective in predicting geometric variables with high accuracy, even when the antenna is placed on tissue, making it a reliable choice for antenna design and optimization.

Table 4.4: Geometrical parameters predicted using the first model

	Free space	With tissue	With tissue inverse
input is S_{11}	0.2859	-0.4013	0.3137
	1.9373	1.8994	0.7653
	2.9819	2.7466	1.9363
	9.118	10.0167	9.9384
	9.9572	10	9.8151
	9.8597	5.5996	8.7726
RMSE	0.3842	1.8074	0.8464
input is Gain	0.0309	0.0927	0.676
	1.8412	1.8320	1.8976
	2.429	2.0636	2.8036
	10.0559	11.1748	8.5928
	9.6690	10.9912	9.7212
	9.6635	11.6794	9.2837
RMSE	0.3104	1.0079	0.7161
input is SAR -		1.3271	0.4741
		3.2753	2.158
		1.0725	2.3389
		8.3203	10.9831
		9.548	9.998
		15.1989	9.1571
RMSE	-	2.4885	0.6277

Table 4.5: Geometrical parameters predicted using the second model

	Free space	With tissue	With tissue inverse
inputs are S_{11} , Gain, and SAR	0.003	-0.0035	0.2595
	2.024	1.8098	1.6326
	3.032	2.8193	2.8892
	9.9779	9.96	9.7353
	10.0166	9.9553	9.7598
	7.8817	5.3274	10.551
RMSE	0.8650	1.9107	0.3281

Table 4.6: Geometrical parameters predicted using the proposed model

	Free space	With tissue	With tissue inverse
inputs are S_{11} , Gain, and SAR	0.0049	0.99	-0.3388
	1.9216	1.7506	1.9679
	2.8299	3.2502	3.0113
	10.0559	10.0112	10.0349
	9.9695	10.1063	10.0736
	9.8645	10.0218	9.8375
RMSE	0.0979	0.4314	0.1576

The prototype of the manufactured antenna placed on the rear arm is illustrated in Figure 4.17. The simulation results were compared to those of the measurement and are reported in Figure 4.18. A good agreement between the simulation results and the measurements is observed. The recorded offset is due to several factors, namely: in the simulation the antenna is placed horizontally 2 mm above a planar phantom of rectangular shape of finite dimensions with three layers whose dielectric parameters are fixed (the frequency dependence is not taken into account) while the measurements are carried out directly on the forearm of an adult with as separation between the skin and the ground plane a shirt whose dielectric properties are unknown and are not taken into account during the simulation, in addition to other factors, namely wiring, connections, equipment, etc.

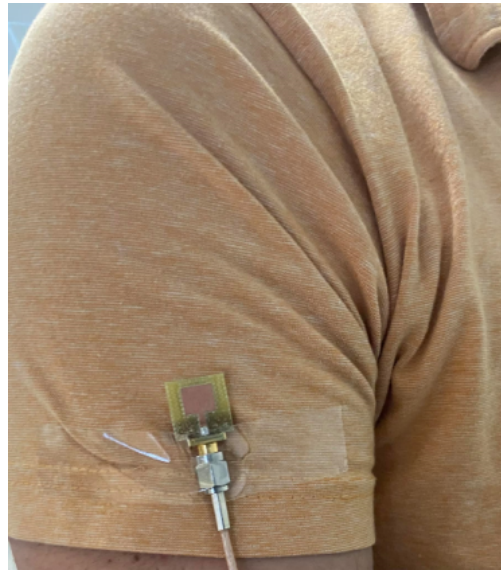


Figure 4.17: Photos of the prototypes fabricated antenna.

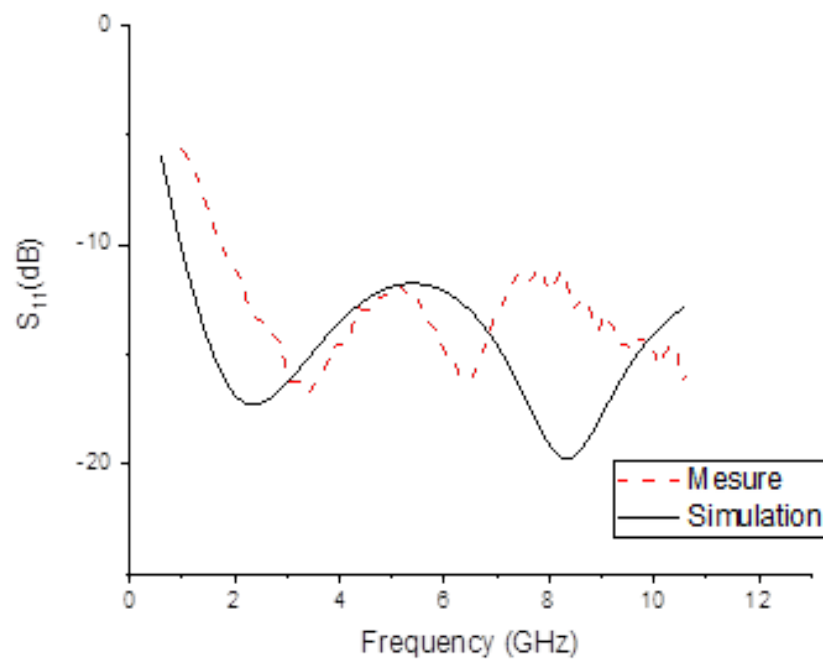


Figure 4.18: Reflection coefficient measured and simulation results.

4.5 Conclusion

This chapter introduced and evaluated inverse neural network models for the multi-objective optimization of biomedical antennas. Three different models were investigated, with the proposed approach showing superior performance in predicting optimal design parameters. Careful dataset preparation and splitting strategies contributed to the robustness of the models.

Application studies demonstrated that the inverse ANN models were able to accurately predict antenna parameters under diverse conditions, including free space, tissue environments, and tissue inverse scenarios. Key metrics such as reflection coefficient, gain, and SAR were reliably estimated, with results showing strong agreement between ANN predictions and HFSS simulations. Experimental validation through the fabrication and measurement of a prototype further confirmed the practical effectiveness of the proposed method.

Overall, the findings underscore the capability of inverse ANN models to address complex, multi-objective optimization challenges in biomedical antenna design. This chapter thus concludes the technical core of the thesis, setting the stage for the general conclusion, which summarizes the main contributions and outlines future research directions.

General Conclusion

This thesis presented a comprehensive study on the design and optimization of miniature biomedical antennas using Artificial Neural Networks. The research addressed the challenges of antenna miniaturization, biocompatibility, Specific Absorption Rate (SAR) compliance, and efficient wireless communication in medical environments.

The first part of the work reviewed the **Fundamentals of Biomedical Antenna Design**, emphasizing the importance of compactness, efficiency, and patient safety. The second part introduced **Machine Learning Methods for Antenna Design**, highlighting how these approaches can reduce computational costs and improve prediction accuracy. The third part explored **Artificial Neural Networks for Antenna Optimization**, providing detailed architectures, training strategies, and case studies such as circular patch antennas, UWB antennas, and dual-band ISM antennas optimized with hybrid ANN-PSO models. Finally, the fourth part presented **Inverse Neural Networks for Multi-Objective Biomedical Antenna Design**, demonstrating how inverse models can predict optimal antenna geometries directly from desired performance targets, with validation through both simulations and experimental measurements.

The findings of this research confirm that ANN-based approaches significantly accelerate the antenna design process while maintaining high accuracy and adaptability. In particular, the use of inverse ANN models demonstrated the potential to directly map performance requirements to optimized antenna structures, a capability that traditional methods cannot

provide efficiently.

Looking ahead, future research can extend this work in several directions. These include integrating deep learning architectures for higher-dimensional problems, exploring novel materials and fabrication techniques for biomedical antennas, and combining ANN-based optimization with real-time adaptive systems. Such advancements will further strengthen the role of intelligent computational methods in the development of next-generation biomedical devices.

In conclusion, this thesis establishes Artificial Neural Networks as a robust and versatile tool for biomedical antenna design, bridging the gap between electromagnetic theory, optimization techniques, and practical healthcare applications.

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