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Machine learning-driven design and performance analysis of microstrip antennas for sub-6 GHz/mm Wave 5G networks

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ABSTRACT

In the realm of modern communication systems, antennas are crucial components, with the microstrip patch antenna being particularly notable for its low profile and seamless integration. Despite its widespread use, designing this antenna involves complex simulations to optimize parameters, requiring significant expertise and consuming considerable time and energy. To streamline this process, machine learning (ML) algorithms are being utilized. This paper introduces an innovative approach that employs ML techniques to design a rectangular microstrip patch antenna operating within the sub-6 GHz frequency range (1-6 GHz) and the millimeter frequency range (28-40 GHz). The antenna design maintains consistent patch dimensions positioned strategically at the center, with a thorough examination of patch length and width to enhance performance. Datasets are meticulously prepared, covering output parameters such as beam area, directivity, gain, and radiation efficiency across the specified frequency ranges. By employing various ML algorithms, this study conducts a comprehensive analysis to identify the most effective algorithm for accurately predicting antenna characteristics. The K-nearest neighbor (KNN) algorithm achieved high accuracy across all parameters: gain at 94.23% under sub-6 GHz and 95.93% under millimeter frequency range, directivity at 99.02% and 98.59%, radiation efficiency at 93.94% and 94.28%, and beam area at 99.07% and 98.59% respectively. These results optimize microstrip antenna designs and enhance understanding of the relationship between design parameters and performance outcomes with ML.

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1. INTRODUCTION

In the domain of computer science and artificial intelligence (AI), a hierarchical structure exists among AI, machine learning (ML) [1], and deep learning (DL). AI is a broad concept focused on developing intelligent systems that replicate human cognitive functions. ML, a subset of AI, focuses on developing algorithms that enable machines to learn and improve from data without explicit programming. Within ML, DL emerges as a specialized field that utilizes deep neural networks, inspired by the structure of the human brain, to automatically learn complex patterns and representations from data. DL, thus, falls under the umbrella of ML, which itself is a subset of the broader AI domain [2]. This hierarchical arrangement illustrates the progressive specialization and advancement in leveraging data for the development of intelligent systems, with DL representing a particularly potent approach within the larger realms of ML and

AI [3]. ML techniques are revolutionizing the field of antennas, introducing innovative methods for design optimization, performance prediction, fault detection, adaptive beamforming, and channel modeling in communication technology [4], particularly in antenna selection for wireless communications [5]. Engineers can efficiently address design challenges, anticipate performance metrics, detect issues, dynamically optimize antenna arrays [6], and enhance the accuracy of channel models through ML. Leveraging ML accelerates antenna development to meet the rigorous demands of modern communication systems, driving advancements in wireless technology.

Many studies explore ML applications in antenna design to streamline the process while maintaining accuracy. ML's ability to minimize errors, predict antenna behavior, and enhance computational efficiency positions it as a transformative tool in antenna engineering [7]. By conducting multiple simulations to gather electromagnetic characteristics and creating a dataset for training ML algorithms, designers can efficiently predict and design antennas that meet desired specifications. This iterative approach offers a faster and more intelligent way to design antennas [8], departing from traditional methods.

Microstrip antennas are compact and lightweight, making them popular choices in communication systems due to their seamless integration with circuit boards. They consist of a metallic patch positioned on a dielectric substrate, allowing for design adjustments to meet specific requirements like frequency, bandwidth, and polarization. Widely utilized across various sectors, microstrip antennas serve diverse applications in wireless communication, radar, remote sensing, radio frequency identification (RFID), medical, automotive, and military fields. They offer efficient signal transmission and reception in diverse environments. However, microstrip antennas face challenges such as limited bandwidth and efficiency, prompting ongoing efforts by researchers to overcome these limitations. Advancements in materials, manufacturing techniques, and signal processing, including ML [9], are driving improvements in microstrip antenna capabilities, ensuring their continued relevance in modern communication technologies.

Analysis of various papers reveals that manual antenna design is both time-consuming and resource-intensive. To address this challenge, the application of ML in antenna design is proposed. The integration of ML techniques into microstrip antenna design holds promise for simplifying workflows, improving performance prediction accuracy, and speeding up optimization tasks [10]-[12]. With ongoing advancements in ML, its fusion with antenna design is anticipated to spur further innovations in wireless communication technologies. Present research initiatives are centered on enhancing the efficiency and capabilities of microstrip antennas in communication systems through the incorporation of ML into antenna design theory [13].

The reaearch approach aims to streamline the design process, with a particular focus on microstrip antennas. The research objective is to optimize the antenna design process by determining the ML algorithm that provides the most accurate predictions for antenna parameters. By identifying the algorithm with the highest precision, our aim is to minimize the necessity for multiple simulations and decrease the time and energy expended in creating top-quality antennas. This method allows us to develop antennas with optimal dimensions in just one iteration, thus improving efficiency and productivity in antenna design.

2. METHOD

A microstrip antenna is composed of essential elements including the patch, substrate, ground plane, feedline, and optionally a matching network as shown in Figure 1. The patch, typically constructed from metal, is positioned on top of a dielectric substrate, with the ground plane situated beneath it. The feedline links the patch to the transmitter or receiver. Optionally, a matching network can be incorporated to enhance impedance matching.

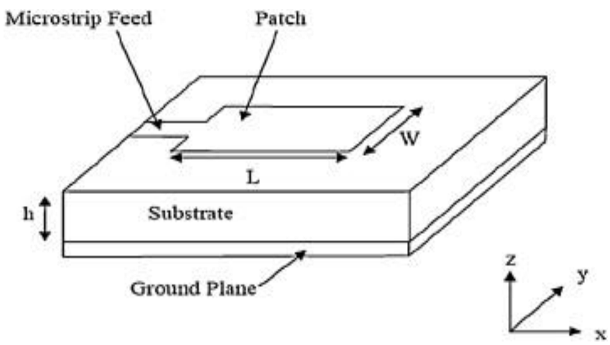

Figure 1. Microstrip antenna [14]

The structure of the antenna governs its radiation pattern, impedance characteristics, and bandwidth. Through meticulous design of these components, microstrip antennas can effectively transmit or receive electromagnetic waves across designated frequency spectrums, catering to diverse application needs [15]. The process of designing microstrip antennas using ansys HFSS [16], [17] encompasses several crucial stages. It starts by creating elements such as the patch, ground substrate, and radiation box, followed by conducting simulations with frequency sweeping. The procedure entails initial geometry setup and material property specification, along with defining excitation sources and meshing the structure. Simulation parameters are configured, and analyses are performed to evaluate antenna performance, including factors like return loss and radiation pattern. Optimization methods may be utilized to enhance performance, and post-simulation tools aid in result analysis. Ultimately, the design undergoes validation and refinement as needed. Ansys HFSS offers a comprehensive platform for microstrip antenna design and optimization across various applications.

2.1. EMtalk patch calculator

The EMtalk patch calculator is a valuable tool in the design process of microstrip antennas. Its primary function is to determine the ideal dimensions for the patch, which is crucial in microstrip antenna construction. By entering parameters such as resonant frequency, dielectric constant, and dielectric height, the calculator provides accurate length and width measurements for the patch [18]. For this specific case, the dielectric constant is 6, the dielectric height is 1.5 mm, and the input impedance is 315 ohms. The calculator finds the values of the length (L_p) and width (W_p) of the patch using the formulas given by (1) and (2), respectively. This data is instrumental in ensuring the precise fabrication of microstrip antennas, thus guaranteeing their performance aligns with specific requirements [19].

$$W_p = \frac{C}{2f_0}\sqrt{\frac{2}{\varepsilon_r+1}} \tag{1}$$

where,
- C is velocity of light,
- f_0 is desired resonant frequency and,
- ε_r is the relative permittivity of the substrate.

$$L_p = \frac{C}{2f_0\sqrt{\varepsilon_{eff}}} - 2\,\Delta L \tag{2}$$

where,
- ε_{eff} is effective dielectric constant of an antenna.
- ΔL is patch length extension.

To calculate the patch length, the effective dielectric constant of an antenna and the patch length extension need to be determined. These values are calculated using the formulas provided in (3) and (4).

$$\varepsilon_{eff} = \frac{\varepsilon_r+1}{2} + \frac{\varepsilon_r-1}{2}\left[1+12\left(\frac{h}{w_p}\right)\right]^{-\frac{1}{2}} \tag{3}$$

where,
- h is substrate thickness and w_p is patch width

$$\Delta L = h{*}0.412\left[\frac{(\varepsilon_{eff}+0.3)\left(\left(\frac{W_p}{h}\right)+0.264\right)}{(\varepsilon_{eff}-0.258)\left(\left(\frac{W_p}{h}\right)-0.8\right)}\right] \tag{4}$$

In the sub-6 GHz frequency range, a dielectric constant of 6 and a height of 1.5 mm are chosen. Conversely, for the millimeter wave frequency range, the dielectric constant remains constant while the height is reduced to 0.5 mm. These parameters play a crucial role in determining the dimensions of the microstrip antenna, which are documented in a table. With the obtained patch dimensions, the microstrip antenna is then designed accordingly.

2.2. Antenna design and created data sets

The Microstrip antenna is designed with specified operating frequency, height, length, and width values, followed by simulations using ansys HFSS. The sweep frequency technique is employed to vary the frequency and observe the antenna's performance across the specified ranges of 1-6 GHz and 28-40 GHz. The flowchart for the research work is as shown in Figure 2.

The designed antenna undergoes simulation to record results, which include gain, beam area, directivity, and radiation efficiency, for each frequency variation. This process results in two datasets: one for the 1-6 GHz range and another for the 28-40 GHz range, capturing the antenna's behavior under different operational conditions. By iterating through various combinations of dimensions, a dataset is generated to serve as the foundation for analysis. ML algorithms are then utilized on this dataset to determine the most accurate algorithm for predicting antenna parameters such as gain, directivity, beam area, and radiation efficiency.

In the careful construction of datasets for microstrip antenna design, two specific frequency ranges were taken into account: 1-6 GHz and 28-40 GHz. For the dataset covering the 1-6 GHz range, each set of antenna parameters is documented in 81 rows, capturing details such as operating frequency, length, width, sweep frequency, gain, beam area, directivity, and radiation efficiency. This meticulous dataset consists of a total of 486 rows, ensuring thorough exploration of the antenna's performance across a range of frequencies within the specified range. The sample dataset for sub-6 GHz frequency range is as shown below in Table 1.

Likewise, in the dataset focusing on the 28-40 GHz frequency range, a consistent structure is upheld with the same eight columns: operating frequency, length, width, sweep frequency, gain, beam area, directivity, and radiation efficiency. Yet, for this elevated frequency band, each operating frequency corresponds to 100 rows of data. Consequently, the dataset for the 28-40 GHz range comprises a total of 1,300 rows, offering a comprehensive and detailed perspective on the microstrip antenna's performance within this particular frequency spectrum. The sample data set createdfor millimeter frequency range is ashown below in Table 2.

This dual-dataset approach not only captures the variability of antenna parameters under different operating conditions but also facilitates a comprehensive analysis that can uncover patterns, trends, and optimal design configurations for both the 1-6 GHz and 28-40 GHz frequency bands. The generated dataset undergoes training with various ML algorithms [20]-[22], including multiple linear regression (MLR), ordinary least squares regression (OLSR), DT, random forest (RF), ANN, ridge regression (RR), lasso regression (LR), support vector regression (SVR), K-neighbors regression (KNR), gradient boosting regression (GBR), elasticnet regression (ER), gaussian progress regression (GPR), RANSAC regression, quantile regression (QR), and isotonic regression (IR) [23]-[25]. Subsequently, the dataset is tested to evaluate accuracy.

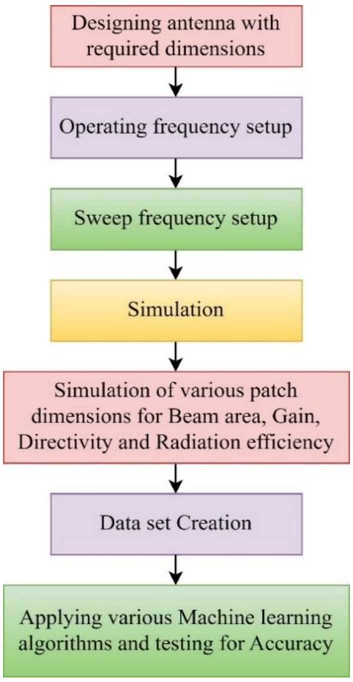

Figure 2. Flow chart for the research work

Table 1. Created data set for sub-6 GHz frequency range

Operating frequency (GHz)	Patch length (mm)	Patch width (mm)	Sweep frequency (GHz)	Gain (dBi)	Directivity (dB)	Beam area (sr)	Radiation efficiency (dB)
1	61	80	1	-19.5844	-14.895486	25.887687	-4.68889186
1	61	80	1.05	-19.002	-14.280274	25.272475	-4.72167899
1	61	80	1.1	-17.7891	-13.647015	24.639216	-4.14203685
-	.	.	.	.	.	.	.
2	30	40	1	-14.4286	-12.244204	23.236405	-2.18443448
2	30	40	1.05	-12.5459	-12.111328	23.103529	-0.43454912
2	30	40	1.1	-10.9552	-11.954492	22.946693	0.999326339
-	.	.	.	.	.	.	.
3	20	26	1.55	4.90961	-4.7269819	15.719183	9.636592233
3	20	26	1.6	5.748265	-4.6999294	15.69213	10.44819486
3	20	26	1.65	6.482228	-4.6736093	15.66581	11.1558378
-	.	.	.	.	.	.	.
-	.	.	.	.	.	.	.
6	9	13	4.9	7.459077	2.80373265	6.514835	2.981710766
6	9	13	4.95	4.448389	2.34830692	7.2846524	0.740840226
6	9	13	5	0.330948	1.33122692	9.7496801	-0.91157242

Table 2. Created data set for millimeter wave frequency range

Operating frequency (GHz)	Patch length (mm)	Patch width (mm)	Sweep frequency (GHz)	Gain (dBi)	Directivity (dB)	Beam area (sr)	Radiation efficiency (dB)
28	1.42	2.86	0.5	-30.3033	-20.830124	31.822325	-9.47321537
28	1.42	2.86	1	-28.9345	-16.048049	27.040249	-12.8864743
.	.	.	.	.	.	.	.
30	1.27	2.67	6	3.983061	-4.8609104	15.853111	8.843971301
30	1.27	2.67	6.5	8.66179	-4.8328075	15.825008	13.49459766
.	.	.	.	.	.	.	.
33	1.08	2.42	2.5	-11.0531	-19.08442	30.076621	8.031369335
33	1.08	2.42	3	-14.3641	-16.937237	27.929438	2.573183315
.	.	.	.	.	.	.	.
36	0.93	2.22	30	15.45909	3.06287665	7.9293243	12.39621572
36	0.93	2.22	30.5	15.79713	3.44060076	7.5516002	12.35652954
.	.	.	.	.	.	.	.
38	0.84	2.1	47.5	7.100958	6.18431047	4.8078905	0.916647801
38	0.84	2.1	48	6.717097	6.07152646	4.9206745	0.645570824
.	.	.	.	.	.	.	.
40	0.76	2	50	5.144772	5.43579453	5.5564064	0.62562502

3. RESULTS AND DISCUSSIONS

The datasets resulting from the design process of microstrip antennas across the sub-6 GHz and millimeter wave frequency spectrums serve as training inputs for various ML algorithms, aimed at assessing their accuracy. Table 3 provides a detailed examination of the predictive performance of various ML algorithms applied to microstrip antenna design across the frequency ranges of 1-6 GHz and 28-40 GHz. These algorithms are tasked with predicting essential parameters such as gain, directivity, radiation efficiency, and beam area.

Within the 1-6 GHz frequency range, MLR provides moderate predictions for gain (0.2316) and directivity (0.6987), while yielding lower values for radiation efficiency (0.1000) and beam area (0.8157). OLSR improves upon MLR, offering higher predictions for gain (0.3487) and directivity (0.7140), along with enhanced radiation efficiency (0.2621) and beam area (0.8243). DT stands out with high predictions across all parameters, excelling in gain (0.8970), directivity (0.9845), radiation efficiency (0.9271), and beam area (0.9878). Similarly, RF demonstrates superior predictive capabilities, yielding high values for gain (0.9421), directivity (0.9820), radiation efficiency (0.9414), and beam area (0.9846). Artificial neural network (ANN) showcases excellent predictive power, particularly in directivity (0.9922) and beam area (0.9892), with competitive values for gain (0.8979) and radiation efficiency (0.8791).

In the 28-40 GHz frequency range, MLR offers moderate predictions for gain (0.2348) and directivity (0.7836), though with lower values for radiation efficiency (0.0444) and beam area (0.7836). OLSR improves upon MLR, providing higher predictions for gain (0.3487) and directivity (0.8186), with enhanced radiation efficiency (0.0372) and beam area (0.8186). DT stands out, excelling across all parameters, especially in gain (0.9118), directivity (0.9664), radiation efficiency (0.8989), and beam area (0.9660). RF mirrors DT's strong predictive capabilities, offering high values for gain (0.9539), directivity

(0.9790), radiation efficiency (0.9353), and beam area (0.9805). ANN shows impressive predictive power, particularly in directivity (0.9706) and beam area (0.9644), with competitive values for gain (0.9125) and radiation efficiency (0.8572). KNR excels with high predictions in gain (0.9593), directivity (0.9859), radiation efficiency (0.9428), and beam area (0.9859). GBR performs exceptionally well, especially in gain (0.9344) and directivity (0.9762), with competitive values for radiation efficiency (0.9026) and beam area (0.976).

Our study identified significant variations in the performance of ML algorithms for forecasting antenna properties. Notably, RF, KNR, GBR, and DT algorithms consistently exhibited superior accuracy. This could be attributed to their ability to capture intricate nonlinear relationships in the dataset. For instance, RF constructs multiple DT and aggregates their predictions, enhancing resilience to overfitting. Similarly, KNR leverages the similarity principle among data points, making it adept at handling localized patterns. GBR sequentially fits numerous weak learners to minimize prediction errors, leading to enhanced accuracy. DT algorithms offer transparency and interpretability, aiding in understanding underlying patterns in antenna design data. Further research is needed to explore these algorithms' unique characteristics and suitability for microstrip antenna design applications.

Table 3. Predicted accuracy values of different algorithms for different parameters

ML algorithms	Gain		Directivity		Radiation efficiency		Beam area	
	1-6 GHz	28-40 GHz	1-6 GHz	28-40 GHz	1-6 GHz	28-40 GHZ	1-6 GHz	28-40 GHz
MLR	0.2316	0.2348	0.6987	0.7836	0.1000	0.0444	0.8157	0.7836
OLSR	0.3487	0.3487	0.7140	0.8186	0.2621	0.0372	0.8243	0.8186
DT	0.8970	0.9118	0.9845	0.9664	0.9271	0.8989	0.9878	0.9660
RF	0.9421	0.9539	0.9820	0.9790	0.9414	0.9353	0.9846	0.9805
ANN	0.8979	0.9125	0.9922	0.9706	0.8791	0.8572	0.9892	0.9644
RR	0.3680	0.2458	0.7297	0.807	0.2371	0.0137	0.8398	0.807
LR	0.2844	0.2424	0.62	0.802	0.1991	-0.00415	0.77	0.8
SVR	0.39	0.24	0.72	0.797	0.2527	0.0088	0.82	0.79
KNR	0.9423	0.9593	0.9902	0.9859	0.9394	0.9428	0.9907	0.9859
GBR	0.9466	0.9344	0.9859	0.9762	0.9053	0.9026	0.989	0.976
ER	0.37	0.34	0.7300	0.8048	0.2372	0.014	0.838	0.8048
GPR	0.7877	0.8994	0.9193	0.9399	0.7803	0.8678	0.8945	0.8909
RANSAC regression	0.3691	0.2695	0.7300	0.8101	0.237	0.050	0.839	0.8101
QR	0.4098	0.3185	0.5468	0.5998	0.3748	0.2798	0.6580	0.5999
IR	0.2088	0.1860	0.2026	0.2281	0.2284	0.03919	0.2194	0.2281

4. CONCLUSION

This study emphasizes the significant impact of ML algorithms on the design process of microstrip patch antennas. It involves crafting microstrip antennas within the frequency ranges of 1-6 GHz and 28-40 GHz using ansys HFSS. Datasets containing various combinations of heights and widths are generated for analysis with different ML algorithms, offering insights into their effectiveness in accurately predicting antenna characteristics.

The outstanding performance of the DT algorithm is evident, with a notable correlation coefficient of 0.9878 in the 1-6 GHz band. Following closely is the RF algorithm, boasting a substantial coefficient of 0.9846, highlighting its reliability. Extending the evaluation to the 28-40 GHz frequency band reaffirms the consistent efficacy of DT, RF, and KNR, while the ANN emerges as a potent predictor.

These findings underscore the critical importance of selecting the appropriate ML algorithm, with DT and RF emerging as robust choices for accurate predictions across diverse frequency bands and antenna parameters. This innovative approach not only enhances the optimization of microstrip antenna designs but also deepens our understanding of the intricate relationship between design parameters and performance outcomes. By seamlessly integrating traditional antenna design with advanced ML capabilities, this research propels the field of modern communication systems towards unprecedented efficiency and informed processes.

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