



SRM VALLIAMMAI ENGINEERING COLLEGE

(An Autonomous Institution)
SRM Nagar, Kattankulathur –603203



Department of Electronics and Communication Engineering

1906810-PROJECT WORK-PHASE II

OPTIMIZATION OF PLANAR ANTENNAS USING MACHINE LEARNING

Under the Supervision of

Dr. RAMESH. S

Professor

ECE Department

Presented By

142221106113-Ranjini.D

142221106115-Rethina Pradhamesh.R

142221106116-Rithika.R

142221106117-Rogini.E

B.E ECE-IV Year/VIII Semester



PRESENTATION OUTLINE



- Introduction
- Literature Review
 - * Summary of Literature Review
- Problem Statement
- Objectives
- Methodology
- Designs and Results
- ML Implementation
- Applications
- Conclusion
- Work Plan
- References



SUSTAINABLE DEVELOPMENT GOALS



SDG NO : 9

Title : Industry, Innovation and Infrastructure

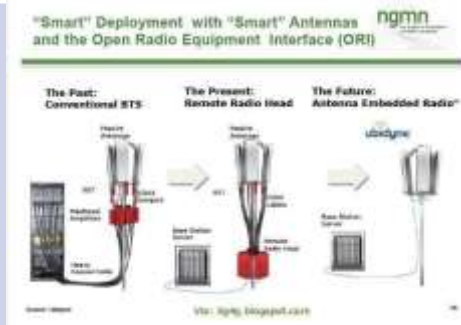
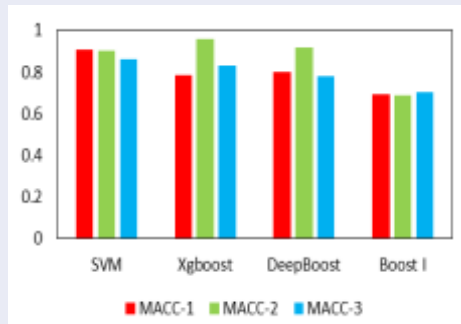
Justification: Optimizing planar antennas using machine learning enhances wireless communication efficiency , supporting advancements in 5G , IOT and satellite systems .This fosters innovation ,strengthens digital infrastructure and accelerates industrial growth.

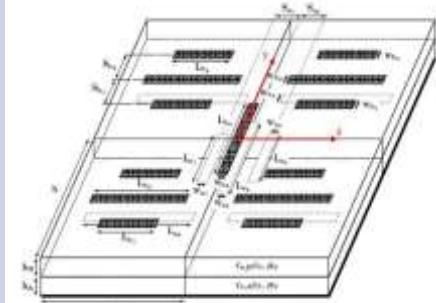
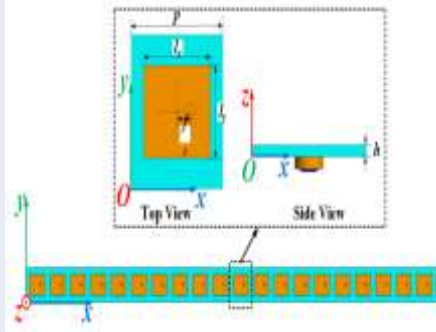



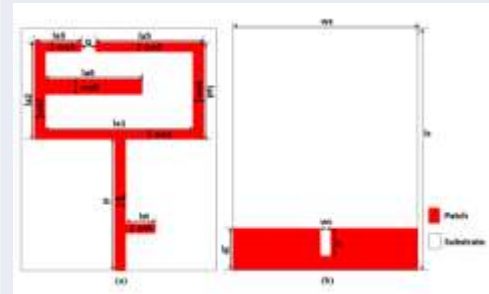
INTRODUCTION



- It is widely used in modern communication systems due to their compact size, lightweight structure, and ease of fabrication.
- However, optimizing their performance parameters like gain, bandwidth, and efficiency is challenging due to complex design constraints.
- Machine learning offers a powerful approach to optimize planar antennas by predicting performance metrics, reducing simulation time, and improving design accuracy.
- ML models can learn from previous simulations and optimize antenna parameters effectively.
- Integrating ML with antenna design can significantly enhance the development of high-performance antennas for applications in 5G, Multiband Antennas and satellite communications.

S.No.	Paper details	Contribution by author	Inference	Structure																				
1.	Christodoulou, C., Rohwer, J. and Abdallah, C., "The use of machine learning in smart antennas". IEEE Antennas and Propagation Society Symposium, 2004.	<ul style="list-style-type: none">• Application of ML in Smart Antennas• Development of LS-SVM for DOA• Adaptation to Environmental Changes• Real-time Problem Solving	<ul style="list-style-type: none">• Increased Fault Tolerance• Enhanced DOA Estimation• Real-time Optimization• Advancement in Smart Antenna Technology• Broader Applicability																					
2.	T. Turki, “An empirical study of machine learning algorithms for cancer identification,” IEEE 15th International Conference on Networking, Sensing and Control (ICNSC), pp.1-5,2018.	<ul style="list-style-type: none">• Application of Machine Learning Algorithms• Performance Evaluation• Data-Driven Insights	<ul style="list-style-type: none">• Improved estimation• Application in design• Resource optimization	 <table><thead><tr><th>Algorithm</th><th>MACC-1</th><th>MACC-2</th><th>MACC-3</th></tr></thead><tbody><tr><td>SVM</td><td>0.95</td><td>0.90</td><td>0.85</td></tr><tr><td>Xgboost</td><td>0.80</td><td>0.95</td><td>0.85</td></tr><tr><td>DeepBoost</td><td>0.80</td><td>0.90</td><td>0.75</td></tr><tr><td>Boost I</td><td>0.70</td><td>0.70</td><td>0.70</td></tr></tbody></table>	Algorithm	MACC-1	MACC-2	MACC-3	SVM	0.95	0.90	0.85	Xgboost	0.80	0.95	0.85	DeepBoost	0.80	0.90	0.75	Boost I	0.70	0.70	0.70
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S.No	Paper details	Contribution by author	Inference	Structure
3.	D. R. Prado, J. A. Lopez-Fernández, M. Arrebola and G. Goussetis, "Efficient Shaped-Beam Reflectarray Design Using Machine Learning Techniques," 15th European Radar Conference (EuRAD), pp. 525– 528, Madrid, 2018.	<ul style="list-style-type: none"> • Application of SVMs in Reflect array Design • Acceleration of Design Process • Modeling of Reflection Coefficient Matrix • Discretization of Angle of Incidence • Mitigation of Overfitting 	<ul style="list-style-type: none"> • Substantial Improvement in Efficiency • Reduction in Design Time • Enhanced Design Accuracy • Potential for Broader Application • Improvement in Cost-Effectiveness 	 <p>Fig. 1. Reflectarray unit cell based on two sets of four parallel dipoles in two different layers</p>
4.	Gan, L., Jiang, W., Chen, Q., Li, X., Zhou, Z. and Gong, S., "Method to Estimate Antenna Mode Radar Cross Section of Large-Scale Array Antennas". IEEE Transactions on Antennas and Propagation, 69(10), pp.7029-7034, 2021.	<ul style="list-style-type: none"> • New Estimation Method • Improvement of SPM • Efficiency • Accuracy • Validation 	<ul style="list-style-type: none"> • Improved estimation • Application in design • Resource optimization 	

S.No.	Paper details	Contribution by author	Inference	Structure
5.	Mohammad Reza Ghaderi and Nasrin Am, "Application of Machine Learning Techniques in Phased Array Antenna" Synthesis: A Comprehensive Mini Review, Journal of Communications, vol. 18, no. 10, October 2023	<ul style="list-style-type: none"> • Identification of Key ML Techniques • Insight into Practical Applications • Highlighting Challenges and Future Directions • Comparison with Conventional Methods 	<ul style="list-style-type: none"> • Efficiency of ML in PAA Design • Adaptability of ML • Insight into Practical Applications • Highlighting Challenges and Future Directions 	
6.	Mohamed. waly, Mohsen Bakouri, Jamel Smida , Bakheet Awad Alresheedi, Tariq Mohammed Alqahtani, Khalid a. Alonzi, and amor Smida “Optimization of a Compact Wearable LoRa Patch Antenna for Vital Sign Monitoring in WBAN Medical Applications Using Machine Learning” , vol 12,June 2024	<ul style="list-style-type: none"> • Design of a Compact Wearable Antenna • Application of Machine Learning • Focus on Medical Applications • Performance Evaluation 	<ul style="list-style-type: none"> • Effectiveness of Machine Learning • Enhanced Medical Monitoring 	



SUMMARY OF LITERATURE REVIEW



Advancements in Antenna Technology:

- Enhanced performance through machine learning.
- Innovative design solutions improve bandwidth, reduce costs, and maintain compactness.

Machine Learning aspects:

- Successful use of SVMs in antenna design and cancer identification.
- Significant improvements in efficiency, accuracy, and cost-effectiveness.

Broader Implications:

- Potential for broader applications in engineering and healthcare.
- Emphasis on the need for larger datasets for improved prediction accuracy in ML-driven antenna design.



PROBLEM STATEMENT



Several Challenges that need to be addressed.

- Limited availability of quality data for training.
- complexity of integrating antenna design with machine learning techniques.
- High computational cost
- Difficulty in interpreting the results generated by machine learning models.

Here are some ways to improve the process of antenna optimization using machine learning algorithms

- Data Augmentation
- Feature engineering
- Ensemble Methods

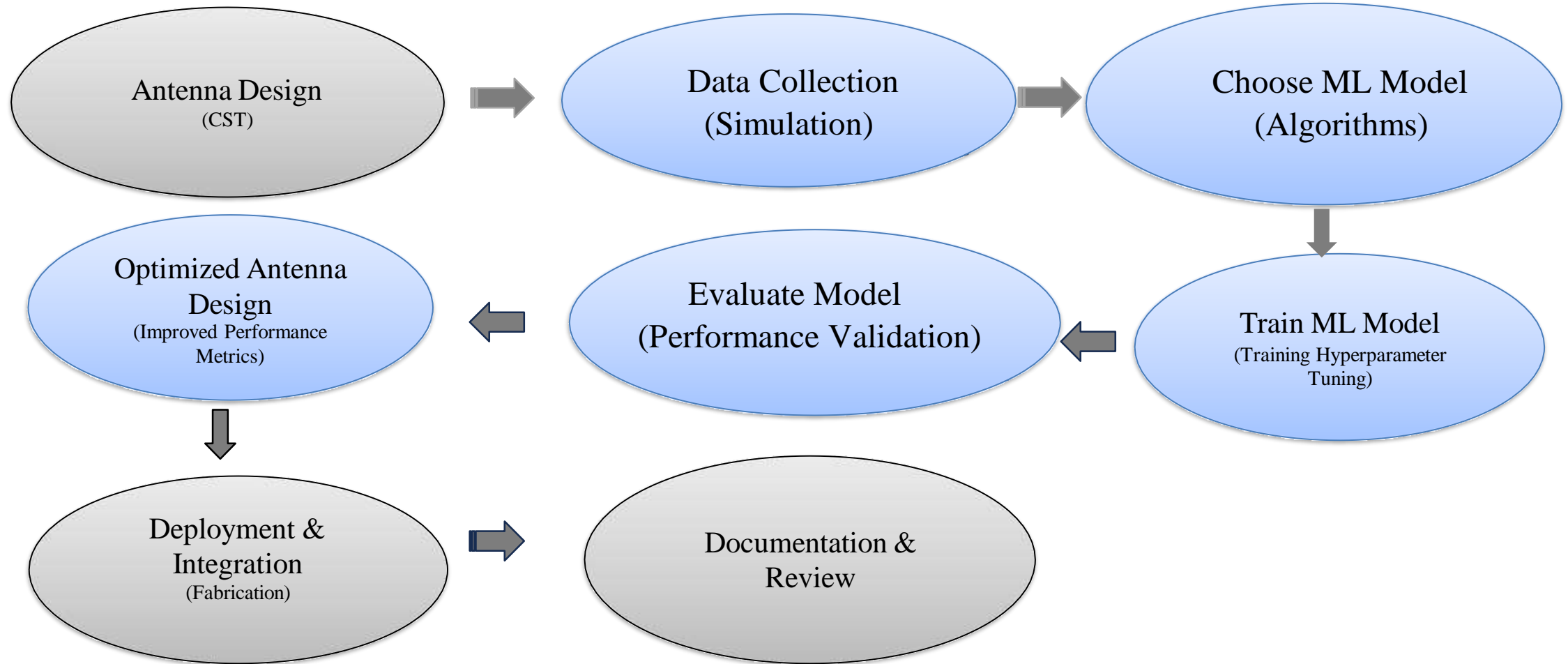


OBJECTIVES



- Optimize planar antennas using machine learning to enhance performance based on specific criteria.
- Identifies optimal design parameters to improve performance.
- Accelerates design process with high accuracy and minimal error.
- Reduces reliance on extensive simulations.
- Automates design exploration and predicts outcomes.
- Guides the process toward optimal solutions efficiently.
- Results in faster, more innovative antenna designs meeting desired specifications.

METHODOLOGY





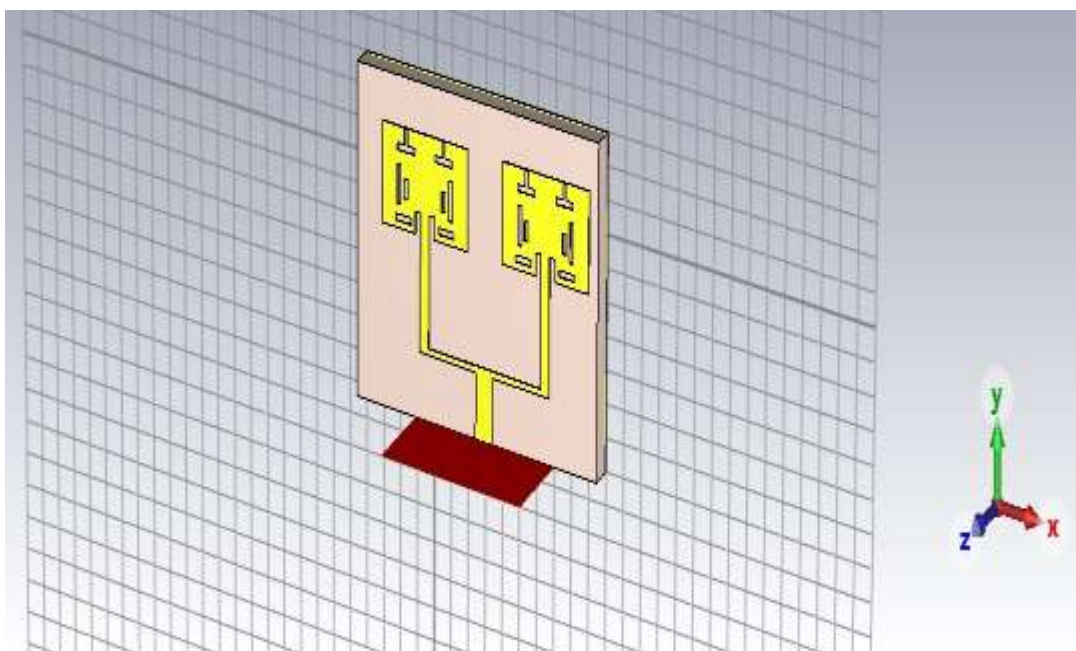
PROPOSED SYSTEM



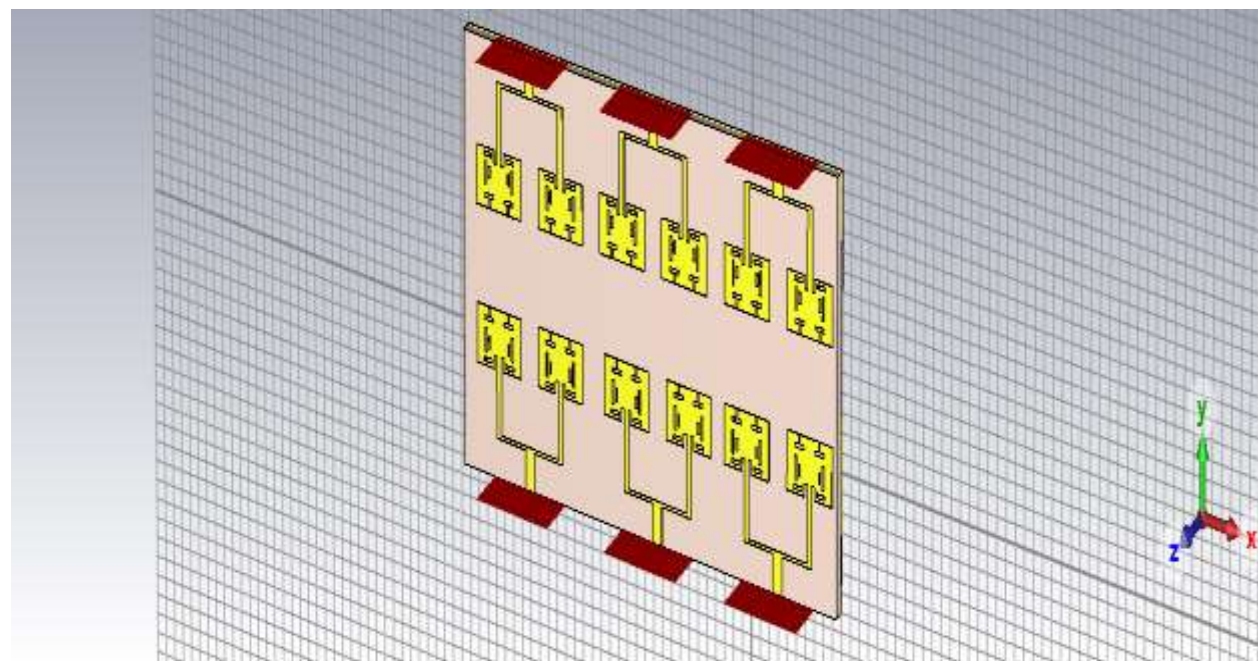
- Integrates machine learning (ML) techniques to optimize the design and performance of MIMO antennas used in 5G mm Wave applications.
- Machine learning algorithms like Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM) are used to identify patterns in the data, optimize antenna parameters, and make predictions for antenna performance under different conditions.
- This data-driven approach provides faster and more accurate optimization, improving the overall efficiency of the antenna design process.



ANTENNA DESIGN

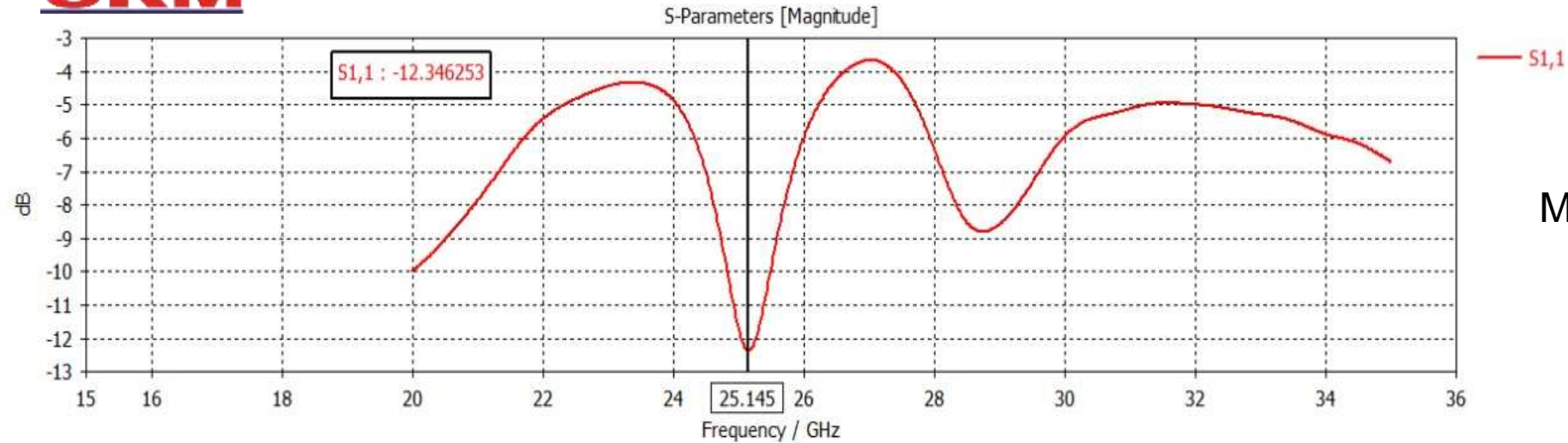


1(a) ARRAY

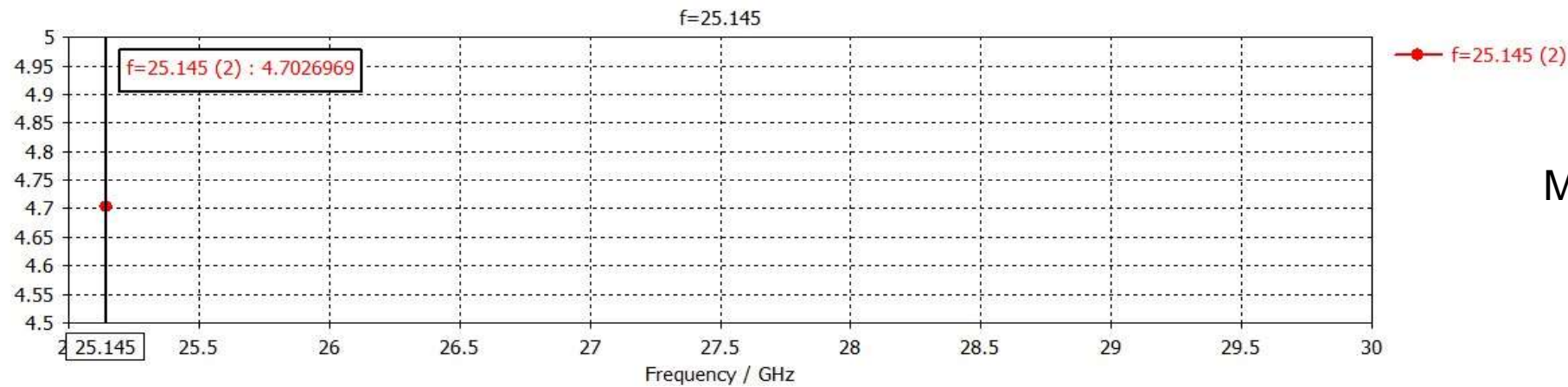


1(b) MIMO

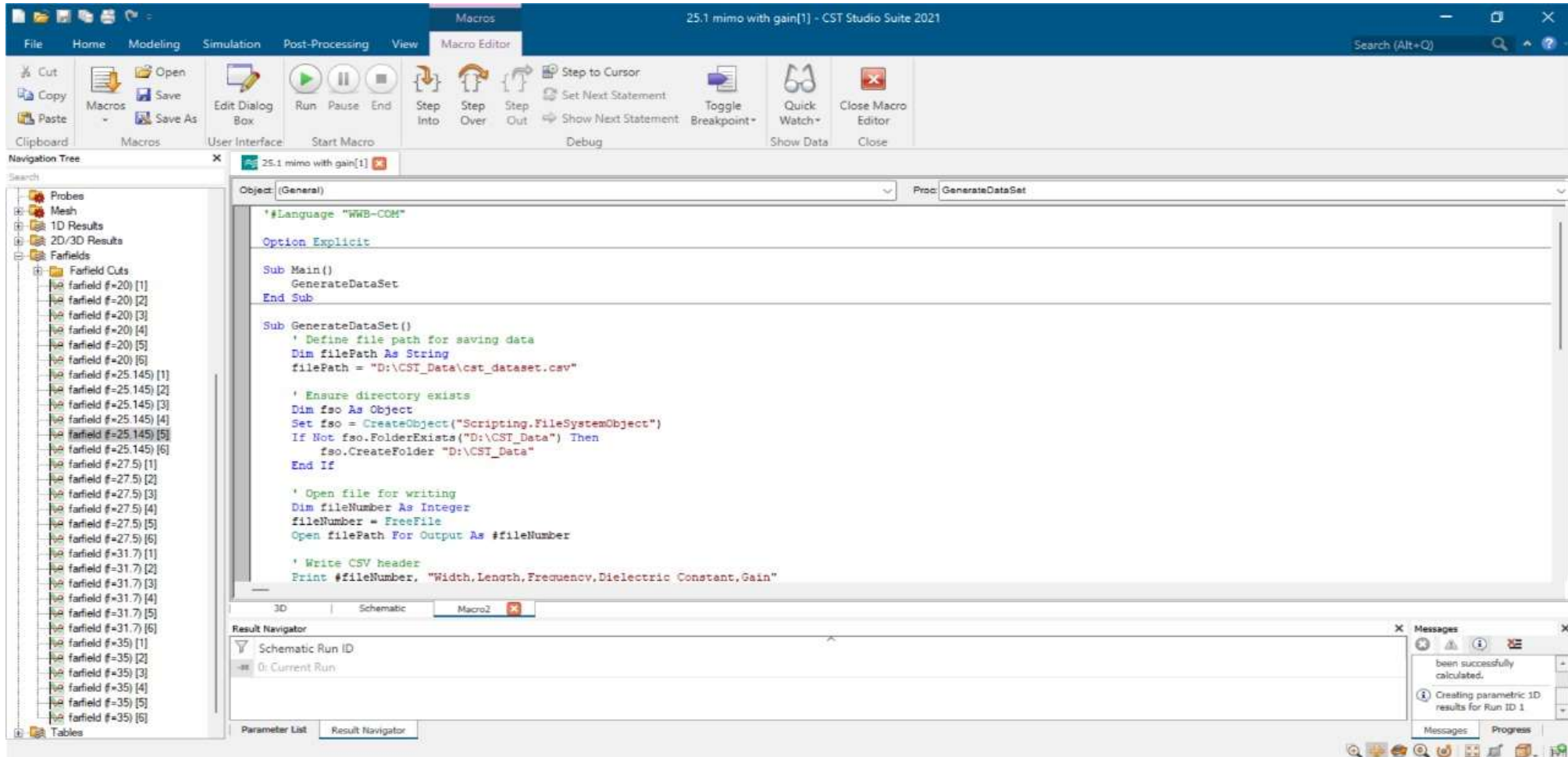
RESULT



MIMO S-PARAMETER

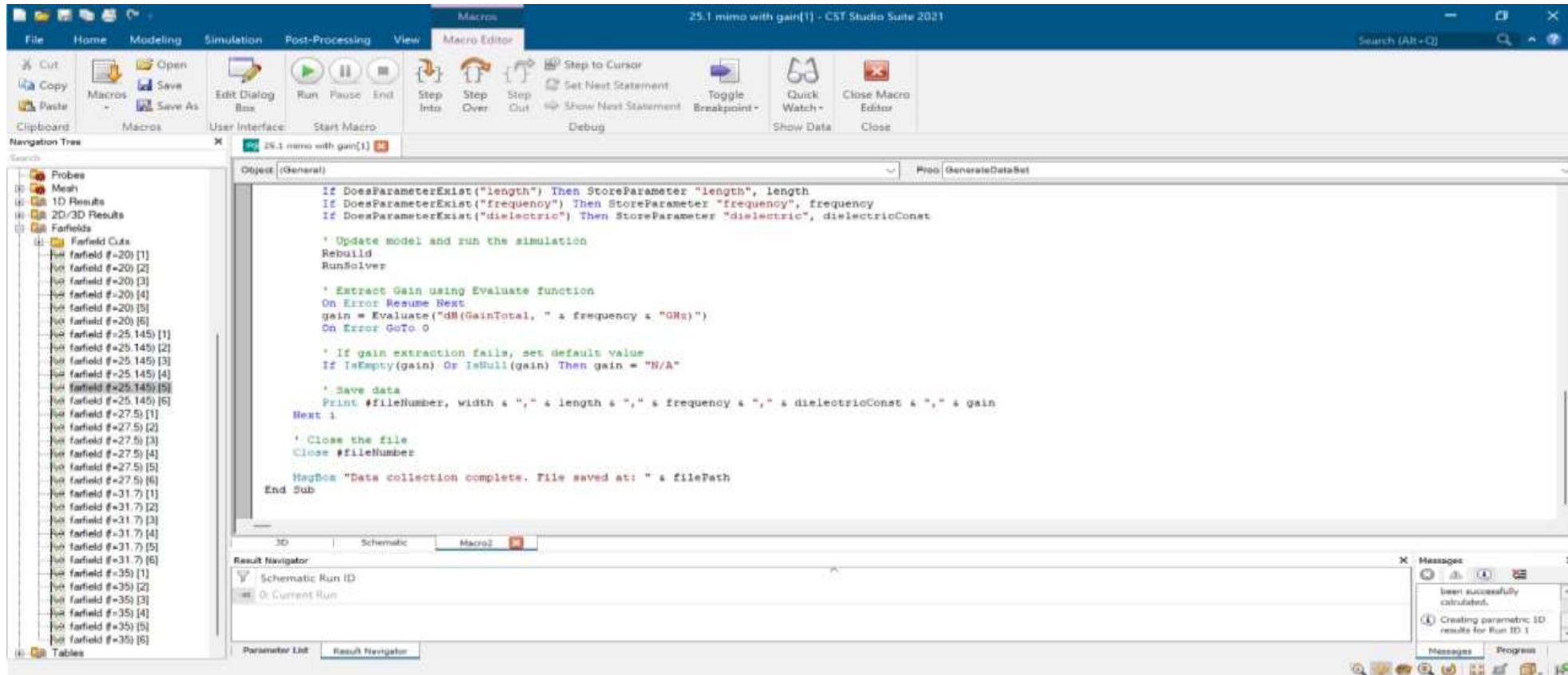


MIMO GAIN





SCRIPT





MACHINE LEARNING IMPLEMENTATION



```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_absolute_error
from xgboost import XGBRegressor,XGBModel
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from matplotlib import pyplot
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

import warnings
warnings.filterwarnings("ignore")
```



MACHINE LEARNING IMPLEMENTATION



```
dataframe=pd.read_csv("synthetic_antenna_data.csv")

print("-----")
print()
print("Data Selection")
print("Samples of our input data")
print(dataframe.head(5))
print("-----")
print()

dataframe.describe()

#checking missing values
print("-----")
print()
print("Before Handling Missing Values")
print()
print(dataframe.isnull().sum())
print("-----")
print()

print("-----")
print("After handling missing values")
print()
dataframe_2=dataframe.fillna(0)
print(dataframe_2.isnull().sum())
print()
print("-----")
```



MACHINE LEARNING IMPLEMENTATION



```
# Step 3: Split the dataset into features (X) and target (y)
x = df.drop('predicted_gain', axis=1) # Features: All columns except 'gain'
y = df['predicted_gain'] # Target: The antenna gain

# Split data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)

## Step 4: Feature Scaling (optional)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Step 5: Regression Models

# 1. Random Forest Regression
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

# 2. K-Nearest Neighbors (KNN) Regression
knn_model = KNeighborsRegressor(n_neighbors=5)
knn_model.fit(X_train, y_train)
y_pred_knn = knn_model.predict(X_test)

# 3. Support Vector Machine (SVM) Regression
svm_model = SVR(kernel='linear')
svm_model.fit(X_train, y_train)
y_pred_svm = svm_model.predict(X_test)
```

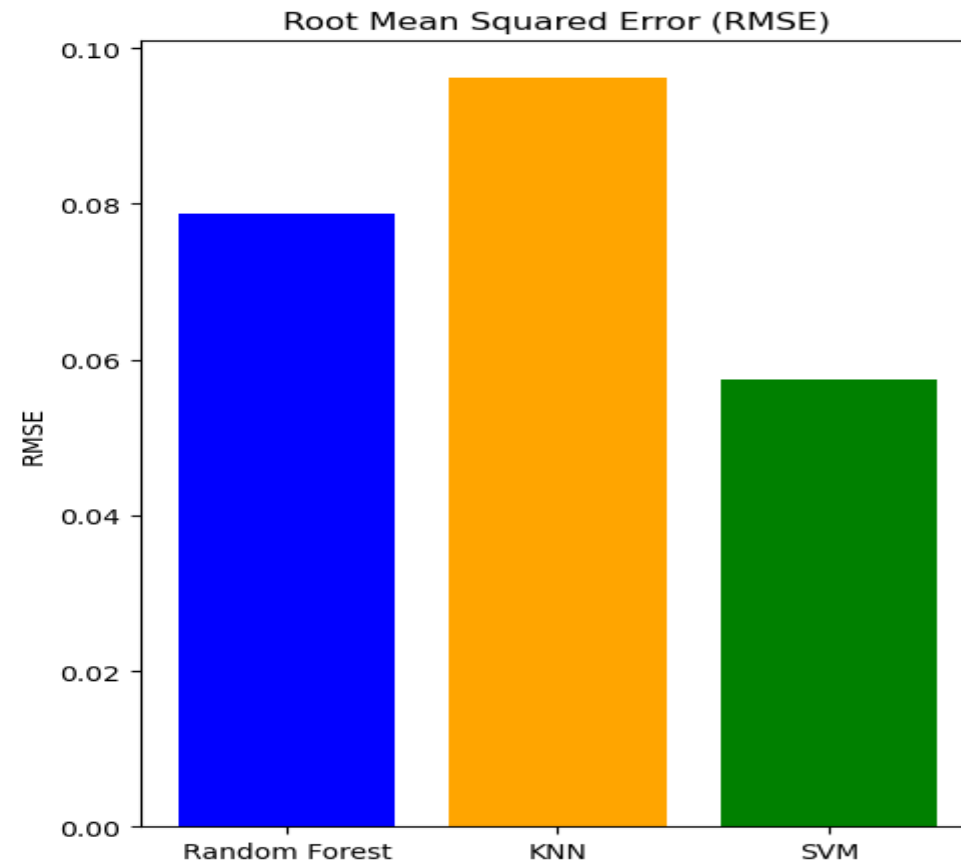
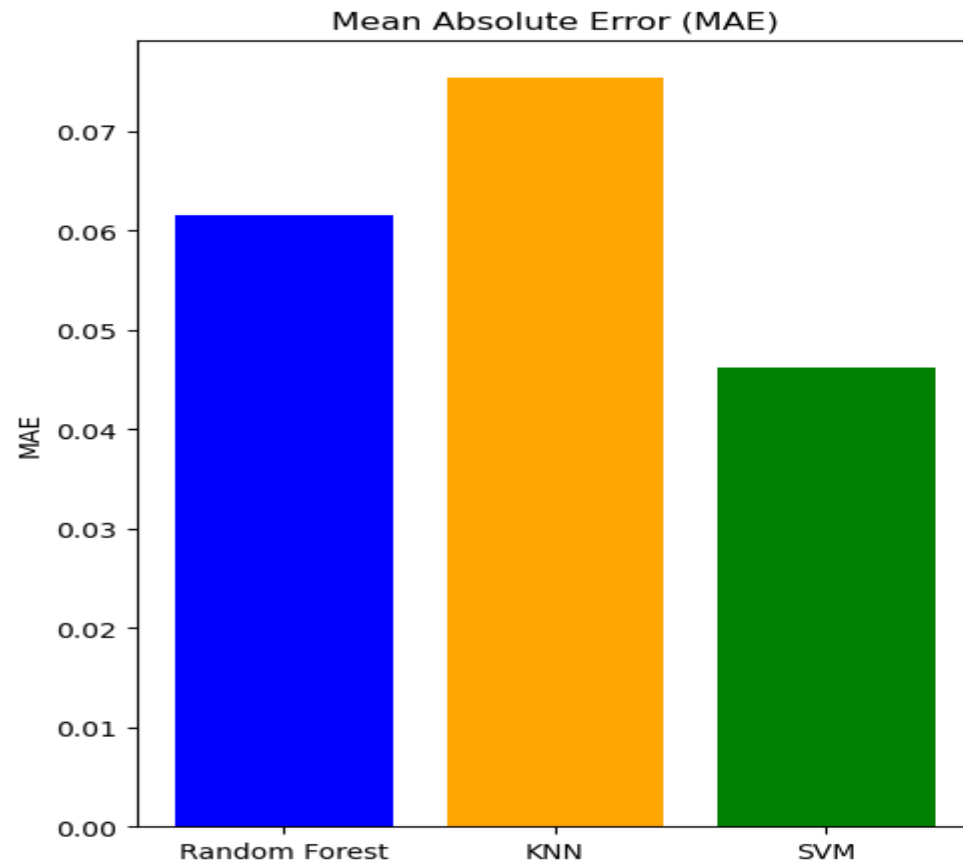
```
# Function to evaluate performance metrics for regression models
def regression_performance_metrics(y_true, y_pred):
    mae = mean_absolute_error(y_true, y_pred)
    rmse = mean_squared_error(y_true, y_pred, squared=False) # RMSE = sqrt(MSE)
    r2 = r2_score(y_true, y_pred)
    print(f"MAE (Mean Absolute Error): {mae:.4f}")
    print(f"RMSE (Root Mean Squared Error): {rmse:.4f}")
    print(f"R² (R-squared): {r2:.4f}")

    # Additional regression performance metrics
    print(f"Train Accuracy (R² on training data): {r2_score(y_train, rf_model.predict(X_train)):.4f}")
    print(f"Test Accuracy (R² on test data): {r2:.4f}")
```

```
Random Forest Regression Performance:
MAE (Mean Absolute Error): 0.0615
RMSE (Root Mean Squared Error): 0.0787
R² (R-squared): 0.8971
Train Accuracy (R² on training data): 0.9834
Test Accuracy (R² on test data): 0.8971
```

```
KNN Regression Performance:
MAE (Mean Absolute Error): 0.0754
RMSE (Root Mean Squared Error): 0.0961
R² (R-squared): 0.8464
Train Accuracy (R² on training data): 0.9834
Test Accuracy (R² on test data): 0.8464
```

```
SVM Regression Performance:
MAE (Mean Absolute Error): 0.0462
RMSE (Root Mean Squared Error): 0.0574
R² (R-squared): 0.9453
Train Accuracy (R² on training data): 0.9834
Test Accuracy (R² on test data): 0.9453
```





MACHINE LEARNING IMPLEMENTATION



```
def calculate_snr(y_true, y_pred):  
    noise = np.subtract(y_true, y_pred) # Residuals (errors)  
    signal = np.mean(y_true) # Signal is the mean of the true values  
    snr = signal / np.std(noise) # SNR = Signal/Noise  
    print(f"SNR (Signal-to-Noise Ratio): {snr:.4f}")
```

Random Forest SNR:

SNR (Signal-to-Noise Ratio): 55.4268

KNN SNR:

SNR (Signal-to-Noise Ratio): 46.0946

SVM SNR:

SNR (Signal-to-Noise Ratio): 76.2476



MACHINE LEARNING IMPLEMENTATION



```
import pandas as pd
import joblib

# Load the pre-trained pipeline (which includes both StandardScaler and SVR)
svm_pipeline = joblib.load("C:\\Users\\rogin\\OneDrive\\Desktop\\Project_27.02.2025\\Sourcecode\\svm_model.pkl") # Ensure this is your pipeline file

# Load the dataset from CSV (make sure it has the same features as used during training)
df = pd.read_csv("synthetic_antenna_data.csv") # Replace with your actual file name

# Drop the 'predicted_gain' column if it exists to avoid conflicts
if 'predicted_gain' in df.columns:
    df = df.drop(columns=['predicted_gain'])

# Convert DataFrame to NumPy array to avoid feature names warning
x = df.values

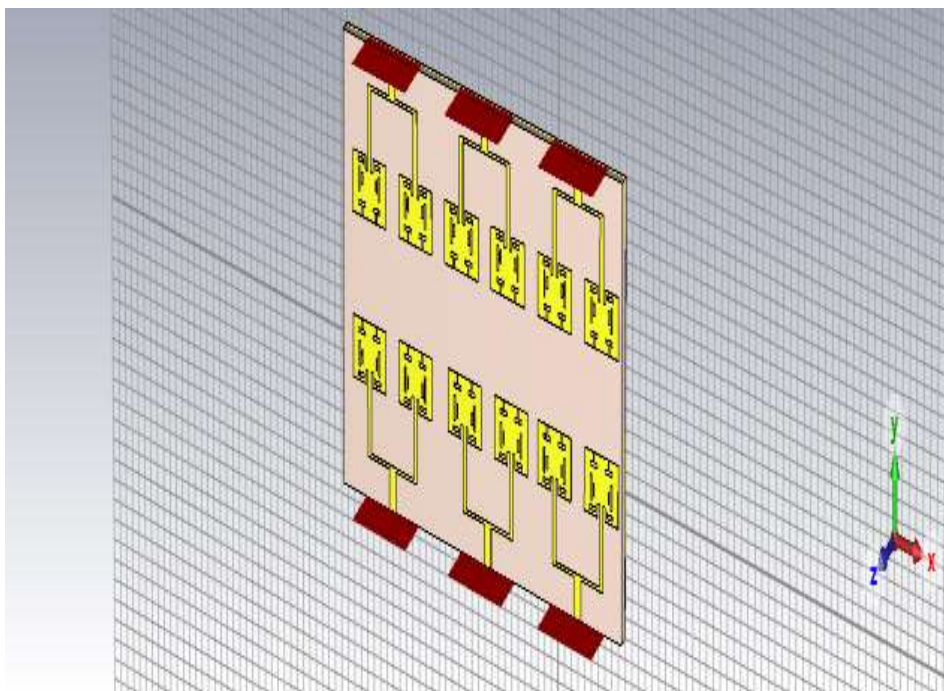
# Predict the gain using the loaded pipeline (the scaler step is applied internally)
predicted_gain = svm_pipeline.predict(x)

# Add the predicted gain back to the DataFrame
df['predicted_gain_new'] = predicted_gain

# Save the results to a new CSV file
df.to_csv("final_svm_gain.csv", index=False)

# Display the first row of the DataFrame
print(df.head(1))
```

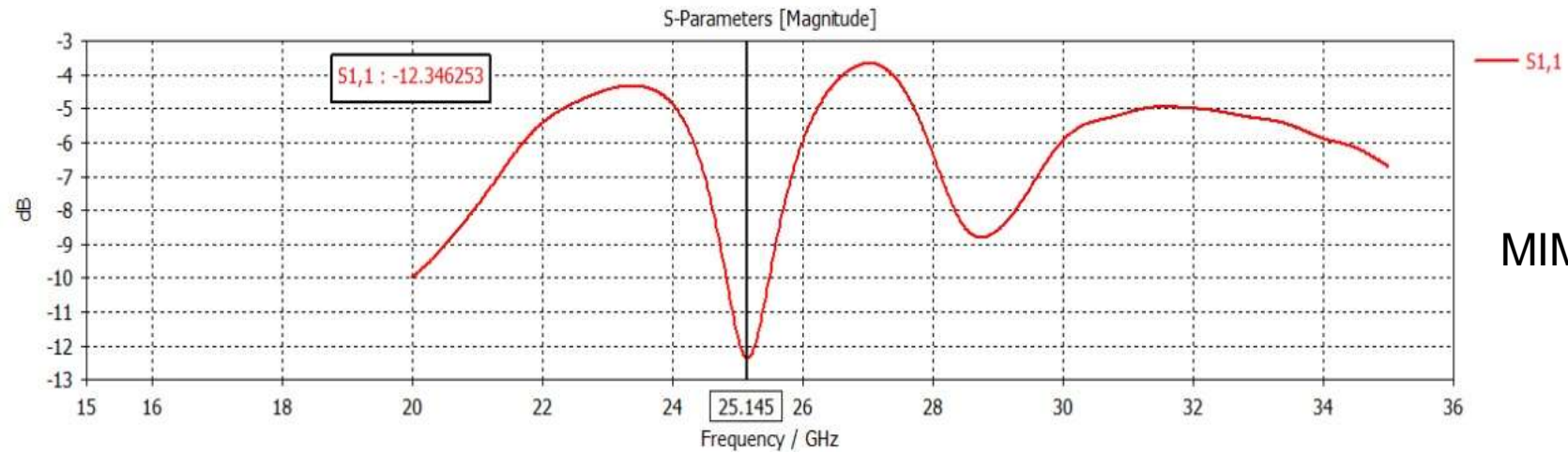

DESIGN AND DIMENSIONS OF THE ANTENNA



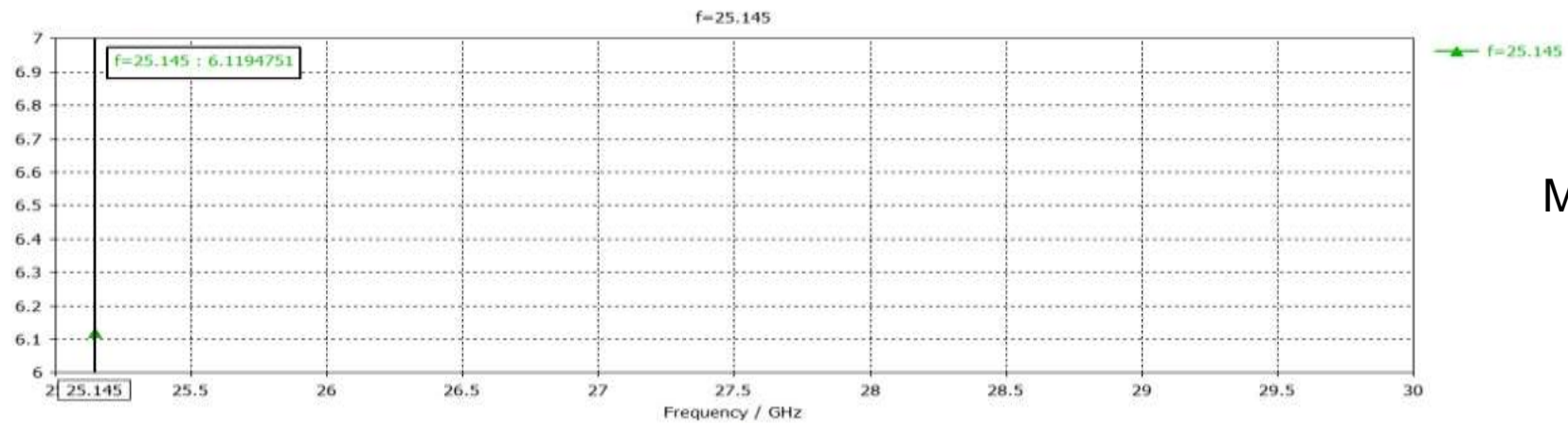
MIMO DESIGN

SPECIFICATION	DIMENSIONS(mm)
Length X Width of Substrate	3.025 X 5
Thickness of the Substrate	0.035
Length X Width of Ground	5.5 X 6
Substrate material	FR-4(Lossy)
Ground material	copper

RESULT



MIMO S- PARAMETER



MIMO GAIN

COMPARISON

PARAMETERS	MICROSTRIP ANTENNA	MIMO ANTENNA PAPER 1	MIMO ANTENNA PAPER 2	OUR MIMO ANTENNA
BANDWIDTH	0.658 GHz	0.578 GHz	0.548 GHz	0.693 GHz
FREQUENCY RANGE	21 to 30 GHz	21 to 30 GHz	21 to 30 GHz	21 to 30 GHz
RESONANT FREQUENCY	25 GHz	25 GHz	25 GHz	25.1 GHz
SUBSTRATE MATERIAL	Rogers RT5880	Rogers RT5880	Rogers RT5880	FR-4 (Lossy)
THICKNESS OF SUBSTRATE	0.030 mm	0.034 mm	0.027 mm	0.035 mm

COMPARISON

PARAMETERS	MICROSTRIP ANTENNA	MIMO ANTENNA PAPER 1	MIMO ANTENNA PAPER 2	OUR MIMO ANTENNA
VSWR	1.02	1.27	1.01	1.63
GAIN	5.7 dB	5.2 dB	5.8 dB	6.1 dB
NUMBER OF DATASETS	150	200	250	500
ALGORITHMS USED	Polynomial regression	Decision tree regression, XGB regression, Nonparametric regression	Decision tree regression, XGB regression, Random forest regression	Random forest regression , KNN regression, SVM regression

APPLICATIONS

- Antenna Design Optimization
 - Miniaturization
 - Multiband Antennas
 - Pattern Synthesis
- Adaptive Beamforming
- Military surveillance radar and airborne radars.
- Remote Sensing and Space Applications
- They support multiple-input multiple-output (MIMO) systems, which enhance data rates and signal reliability.
- Drones and UAVs use patch antenna arrays for long-range communication and navigation.
- Patch antennas are utilized in wireless body area networks (WBAN).

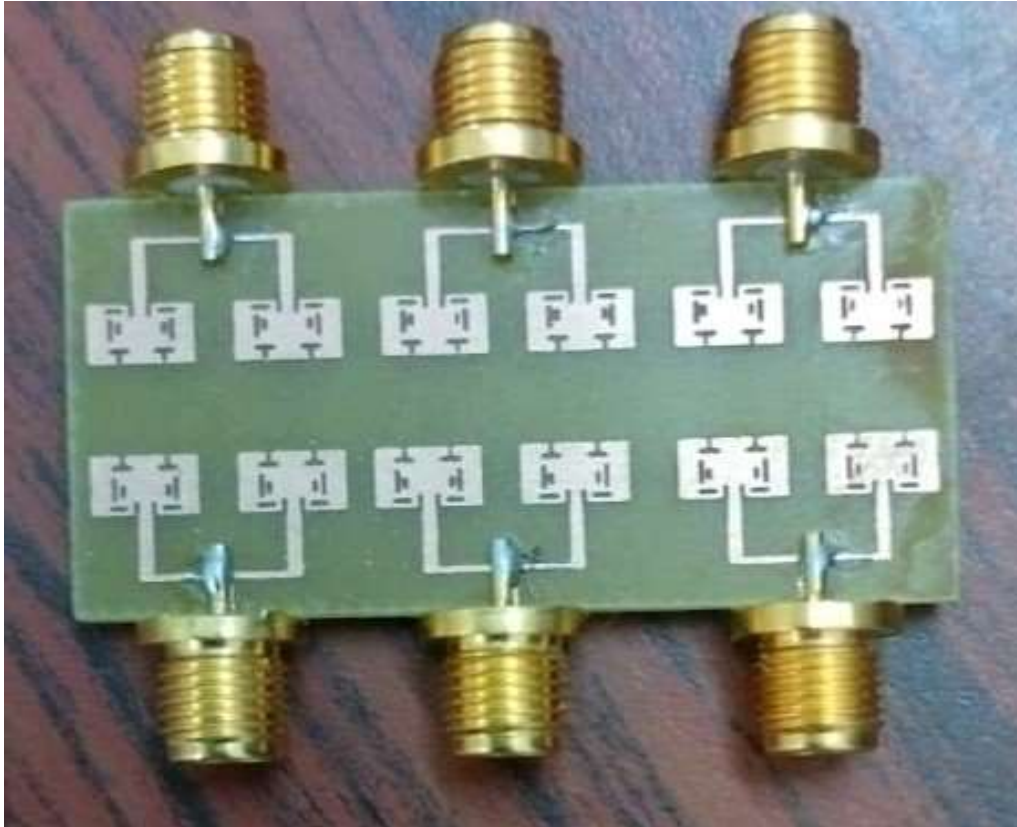


CONCLUSION

- Enhanced performance metrics: gain, bandwidth, radiation patterns.
- ML techniques reduce design time and computational resources.
- Adaptable to various design constraints and objectives.
- Enables exploration of innovative and unconventional antenna designs.
- Improve model accuracy and explore sophisticated algorithms.
- Integrate ML with other optimization techniques for further advancements performance.

S Parameter (dB)	25.1
VSWR	1.63
Bandwidth (GHz)	0.693
Gain without ML Optimization (dB)	4.7
Gain with ML Optimization (dB)	6.1
ML Accuracy (%)	98

FABRICATION OF ANTENNA

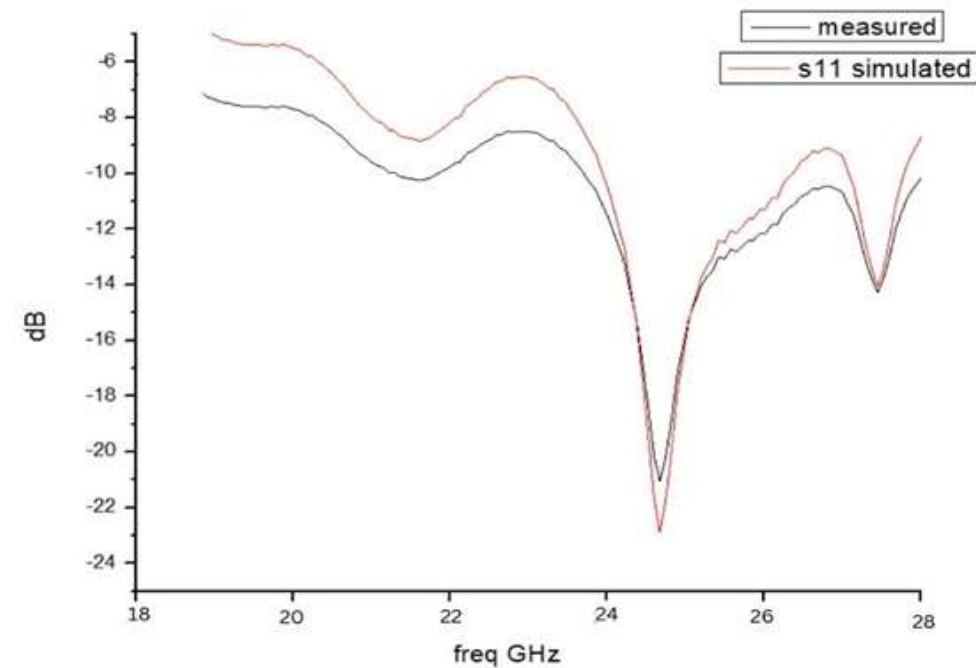
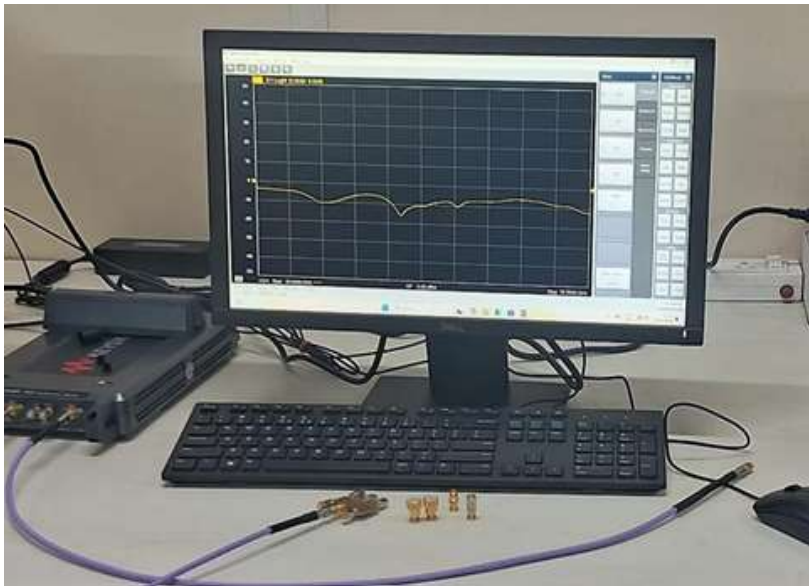


FRONT VIEW

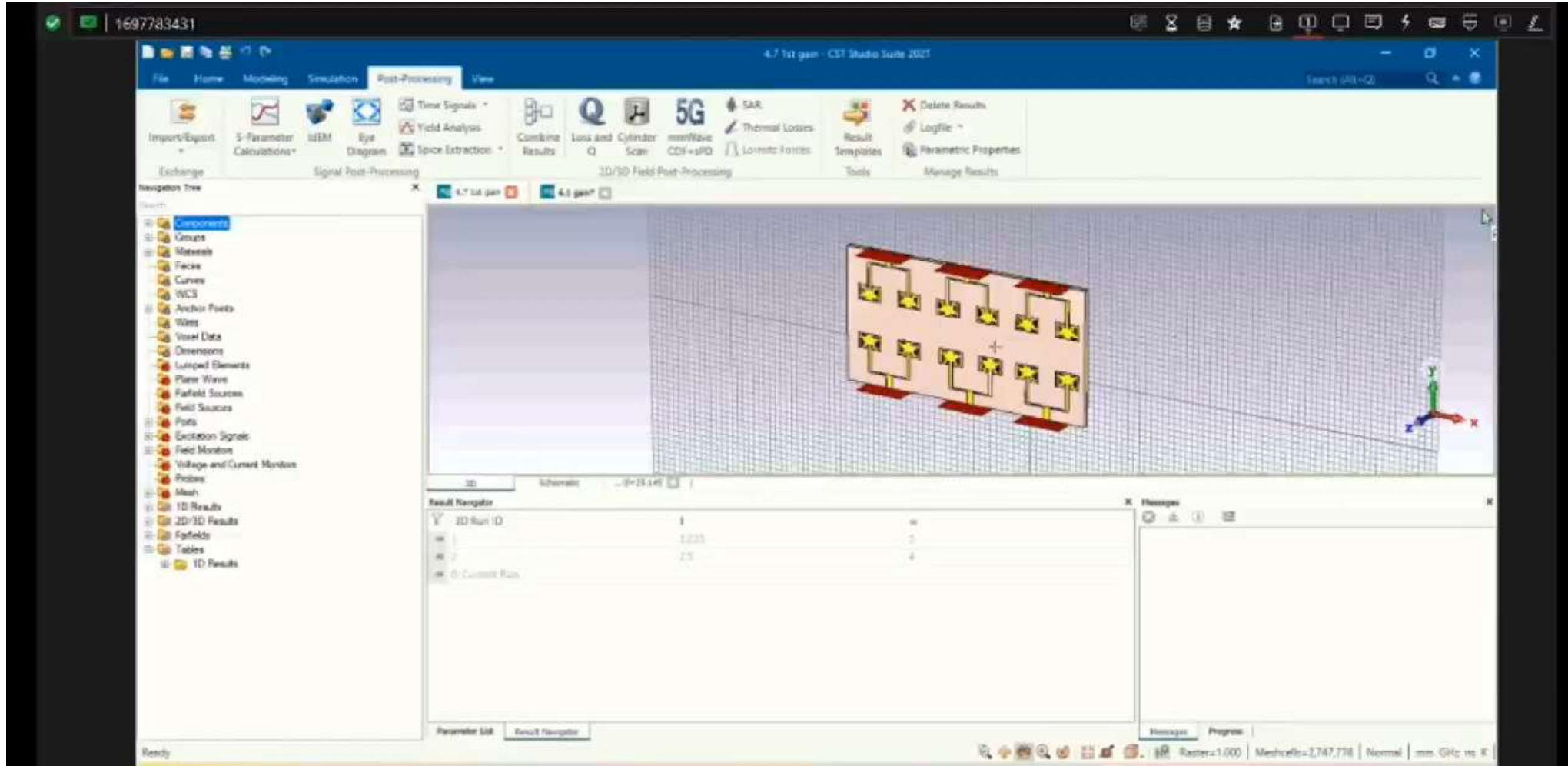


BACK VIEW

Once fabricated, the antenna undergoes testing to validate its performance against simulation data. Key parameters such as return loss (S_{11}), gain, bandwidth are measured using Vector Network Analyzers (VNA).



SIMULATION VIDEO





WORK PLAN



S.NO	Month	Work to be completed (2025)
1	January	Aim, Objectives, Literature Survey, Work Plan, References
2	February	High level Design of the Project, Simulation Output and ML Implementation and Presentation
3	March	Project demonstration, Publication, Project Report Submission, Project Work Plan Submission



REFERENCES



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3. H. Liu, Y. Liu and S. Gong, “An ultra-wideband horizontally polarized omnidirectional connected vivaldi array antenna,”International Symposium on Antennas and Propagation (ISAP), 2016.
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5. D. R. Prado, J. A. Lopez-Fern ´andez, M. Arrebola and G. Goussetis, “Efficient Shaped-Beam Reflectarray Design Using Machine Learning Techniques,”15th European Radar Conference (EuRAD), pp. 525– 528, Madrid, 2018.



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8. Mohammad Reza Ghaderi and Nasrin Am, "Application of Machine Learning Techniques in Phased Array Antenna' Synthesis: A Comprehensive Mini Review, *Journal of Communications* "vol. 18, no. 10, October 2023.
9. Mohammedi. waly, Mohsen Bakouri, Jamel Smida , Bakheet Awad Alresheedi, Tariq Malqahtani, Khalid a. Alonzi, and Amor Smida "Optimization of a Compact Wearable LoRa Patch Antenna for Vital Sign Monitoring in WBAN Medical Applications Using Machine Learning" , June 2024.

Ranjini. D, Rethina Pradhamesh. R, Rithika. R, Rogini. E “Optimization of Planar Antennas Using Machine Learning”, in ISTE sponsored two days National Conference on “New Horizons in Interdisciplinary Societal Innovations in Engineering (NHISIE-2025)” held on 20th March, 2025.





Thank You