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RESEARCH ARTICLE

Microwave Antenna-Assisted Machine Learning: A Paradigm Shift in Non-Invasive Brain Hemorrhage Detection

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ABSTRACT Brain hemorrhages have become increasingly common and can be fatal if left untreated. Current methods for monitoring the progression of the disorder that rely on MRI and PET scans are inconvenient and costly for patients. This has spurred research toward portable and cost-effective techniques for predicting the current stage and malignancy of the hemorrhages. In this study, simulated S-parameter data obtained from a two-antenna system placed over the head is used in conjunction with machine learning to detect the dielectric changes in the brain caused by hemorrhage non-invasively. Several machine learning classifiers are used to analyze the data, and their performance metrics are compared to determine the optimal classifier for this case. The study revealed that Decision Tree, KNN, and Random Forest classifiers are better than SVM and MLP classifiers in terms of accuracy, precision, and recall in predicting Brain hemorrhage at the most probable locations. Contrary to conventional microwave imaging systems requiring several antennas for brain hemorrhage detection, this study demonstrates that integrating machine learning with microwave sensors enables accurate solutions with a reduced antenna count. The results present a transformative strategy for monitoring systems in clinics, where a simple, safe, and low-cost microwave antenna-based system can be intelligently integrated with machine learning to diagnose the presence of Brain hemorrhage.

INDEX TERMS Brain hemorrhage, wearable devices, antenna systems, machine learning classifiers.

I. INTRODUCTION

The monitoring and diagnosis of diseases in the biomedical sector have been made significantly easier by microwave-based technology, which has been successful in achieving the research goal that was set forth for it [1]. In the monitoring of respiratory health [2], [3], bone fracture detection [4], [5], breast cancer detection [6], [7], and the detection of a variety of other abnormalities [8], the work using this technology has shed new light in being a future role model in medical diagnostics. Current diagnostic methods in hospitals for detecting illnesses or abnormalities in human bodies are

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lengthy and involve collecting various types of medical data, including blood tests, ECG, X-RAY, USG, and MRI scans, to determine the disease and its severity. Unusual bodily functions or discomfort in a patient may indicate a potentially fatal condition. Early detection can prevent the patient's condition from worsening severely. Microwave technology has become increasingly prominent in the last decade due to its ability to offer portability, safety, cost-effectiveness, and early illness detection.

The brain, heart, lungs, liver, and kidneys are vital organs that sustain the body's health. The brain is the primary organ in the human nervous system responsible for regulating various functions such as interpretation, synthesis, regulation, decision-making, and directing the body. Any abnormalities related to the brain require immediate attention for correction. Brain hemorrhage, which is the major cause of death and deformity affecting the brain's primary cells, is currently one of the greatest concerns [9]. It is a severe medical illness that occurs when a blood vessel gets ruptured, resulting in the build-up of blood in various parts of the brain. The brain is enclosed by multiple layers of protection, including the skin, fat, bone, and three layers of brain tissue: the dura mater, arachnoid, and pia mater. The ventricles of the brain contain cerebrospinal fluid (CSF) that safeguards the brain from potential damage caused by accidents, brain tumors, strokes, or high blood pressure. Factors like age, blood thinners, and alcohol increase the risk of brain hemorrhage which can result in unconsciousness or even death [10]. The suggested research focuses on two locations of Brain Hemorrhage that are prevalent in the majority of instances. Bleeding can occur within the brain's interior areas as well as between its protective layers, suggesting a similar prototype of a spherical anomaly in the mentioned places [11]. In recent studies, the total incidence of intracerebral hemorrhage (ICH) was measured at 19.1 per 100,000 people [12] and this rate did not significantly change throughout the studies. Both the in-hospital mortality and one-year fatality rates were found significantly high (32.4 % and 45.4 % respectively). The fatality rate was 49.5 % after two years. Just 14.5 % of patients were able to be released back to their homes [12].

Methods such as computer tomography (CT), magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), positron emission tomography (PET), single photon emission computed tomography (SPECT) and electroencephalography (EEG) are examples of common brain imaging techniques. Some of their disadvantages include emitting ionizing radiation and having a bulky and costly setup. The focus of current and upcoming trends is on either the investigation of novel methods to circumvent these constraints or the combination of these drawbacks into multi-modal approaches.

In the past two decades, microwave has been capable of providing portable, safe, cost-effective, and early detection of a wide range of diseases [13], including cardiovascular disease [14], breast cancer [7], brain diseases and chronic diseases like diabetes [15] etc. Microwaves possess the potential to diagnose diseases due to their ability to penetrate human body tissues.

In recent times, many researchers have conducted studies to diagnose the presence of a brain stroke or brain hemorrhage using microwave techniques [16], [17], [18]. However, these are microwave systems with more antenna units for microwave imaging (MWI) of human heads. Due to the utilization of multiple antennas, the overall configuration becomes complex and bulky.

With the goal of improving accuracy and performance while enabling real-time monitoring of biological problems and vital signs in the biomedical field, several artificial intelligence (AI) techniques have been integrated with microwave technology [19], [20], [21].

This article introduces a method that uses microwave technology for the non-invasive identification of brain hemorrhage, utilizing simulated data for validation. The diagnostic system is configured using a microwave sensor system and a machine learning-based framework. The microwave sensor system comprises two bow-tie antennas with resonance-based reflectors (RBRs) operating within the 1.5 - 3.17 GHz range (70.5%) and a peak gain of 5.7 dBi to collect the Transmission Coefficient (S_{21}). Using two antennas enhances portability and eliminates the drawbacks of employing multiple antenna units. To improve the effectiveness of medical investigations, various potential alterations to the anomaly's size and location have been considered. The machine learning processing unit identifies three probable hemorrhage sites based on scattering parameters obtained from the antennas: left subdural, right subdural, and intra-cerebral, which have higher risks of bleeding. Various machine learning classifiers, including Decision Tree, KNN, and Random Forest, effectively predict brain hemorrhage in the expected regions.

In the upcoming section, the configuration of the microwave sensor system has been described including crucial information about the human brain and hemorrhage, antenna selection, antenna performance, and orientation of antennas for maximizing its effectiveness in detecting the probable locations of the hemorrhages. In further sections, machine learning for microwave systems, the proposed machine learning framework utilizing different machine learning classifiers, and their performance metrics are described.

II. CONFIGURATION OF THE PROPOSED MICROWAVE-BASED MODEL

This section describes the processes that are utilized in the EM simulations to obtain S-parameter data, as well as the generation of analytical hemorrhage in the head models.

Subdural and intracerebral bleeding are two critical sites for the progression of brain hemorrhage, which poses a life-threatening risk to individuals. They can also occur without any external injury. Subdural hemorrhages occur in the brain's outer lining near the skull, while intra-cerebral hemorrhages occur in the brain's core region.

TABLE 1. Comparsion table for microwave-based system for hemorrhage detection.

Ref.	System configuration	Antenna number	Frequency	Background Medium	ML model
[22]	Multistatic approach with waveguide antennas, switching circuit, and VNA	177	0.9-1.8 GHz	Matching liquid	NA
[23]	Multistatic system with printed monopole antennas connected to a two-port vector network analyzer through a switching matrix	12	1-1.75 GHz	Matching liquid	NA
[24]	Multistatic approach with folded parasitic antennas, switching circuit, and VNA	16	1-2.4 GHz	Air	NA
[25]	Microwave imaging system composed by coaxial-fed slot bow-tie antennas, switching matrix, and VNA	10	1 GHz	Air	2-step LBE based classification using SVM
[26]	Microwave imaging system with broadband antennas, switching matrix and VNA	12		Matching liquid	Supervised learning based classification
[27]	Microwave imaging system with compact wideband microstrip patch, switching matrix and VNA	8	0.9 - 3 GHz	Air	SpaceDivision-Based Decision-Tree Learning Method
[28]	Transmission coefficient analysis with antennas and VNA	2	1.55-2.05 GHz	Air	NA
This work	Transmission coefficient (Magnitude and Phase) analysis with Bow-tie antennas with RBR	2	1.5 - 3.17 GHz	Air	SVM, MLP, DT, KNN, GB, and RF

Subdural hemorrhage can occur in any age group [2], while those over 50 are at higher risk for intracerebral hemorrhage, which increases with each decade of life [1].

The proposed system targets the detection of the three most probable brain hemorrhage locations (left subdural, right subdural and intra-cerebral) by processing transmission coefficient S_{21} parameter (both magnitude and phase) using the machine learning algorithm. Two wearable antenna sensors, a vector network analyzer (VNA), and a processing unit (PU) are the components that comprise the presented antenna-based system shown in Fig.1. CST Microwave Studio [29] is utilized to develop and simulate the antenna-based system with head models (healthy i.e., without abnormality, and patient head models with hemorrhage) and collect the required S-parameter viz., transmission coefficient (S_{21}). To simulate bleeding, an analytical spherical blood accumulation is implanted in the head model of Gustav (a male body model from the CST voxel family). This is done while taking into account three different locations in the patient's brain that have a higher likelihood of developing a hemorrhage.

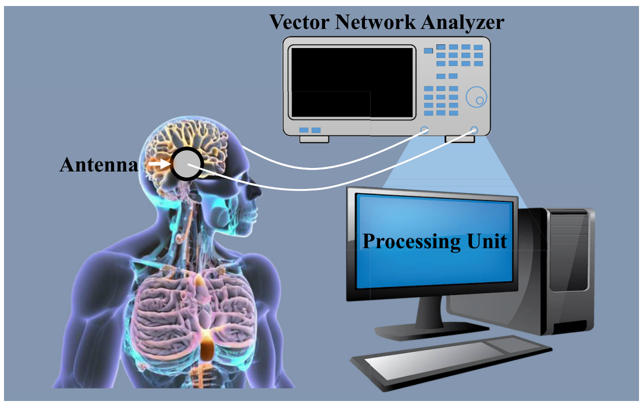


FIGURE 1. Proposed antenna-based diagnostic system for non-invasive detection of Brain Hemorrhage using Machine Learning.

A. THE HUMAN BRAIN AND HEMORRHAGE

The brain and spinal cord are vital components of the human nervous system. The brain is the central element responsible for interpreting, synthesizing, controlling, decision-making, and communicating decisions to other body parts. Deciphering the architecture of the human brain is highly challenging. The brain regulates the body's organs and enables it to perceive and react to external stimuli. The brain comprises the cerebrum, cerebellum, and brainstem [30].

The Head model comprises different tissue layers such as Skin, fat, bone, brain, and other tissues. The cross-sectional view of the head model (Gustav), available in CST microwave studio [29], is shown in Fig. 2. It is widely known that the skin layer is both highly conducting as well

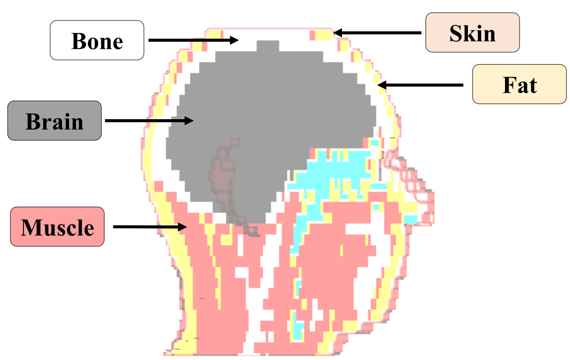


FIGURE 2. Cross-sectional view of the human head model available in CST.

TABLE 2. Dielectric properties of various tissue layers of the head model in 2.4 GHz ISM band.

Tissue	Conductivity (S/m)	Relative Permittivity	Loss Tangent
Skin	1.440	38.063	0.283
Fat	0.102	5.285	0.145
Bone	0.384	11.41	0.252
Brain	1.189	36.226	0.246
Muscle	1.705	52.791	0.241
Blood (Hemorrhage)	2.502	58.347	0.321

as lossy, whereas the fat layer and the bone layer have a lower dielectric constant [31]. To get the optimal variation in transmission coefficient S_{21} (both magnitude and phase), the electromagnetic wave must penetrate through all of the different tissue layers that are being taken into consideration as well as bleeding. The electrical characteristics of various brain layers and the hemorrhage are studied [32] (at 2.4 GHz ISM band) and listed in Table.2.

The analysis and performance of a wearable antenna surrounded by biological tissues causing signal loss differ from those of a free-space antenna. Therefore, it is important to undertake an EM near-field study [33]. Using CST Microwave Studio [29], a 3-D human head model has been incorporated into the antenna system design. This model comprises the following primary head tissues: skin, skull, muscle, fat, bone, blood, and brain tissues. Human tissues can be classified into two categories based on their water content: high-water content tissues (e.g. skin and muscle) and low-water content tissues (e.g. fat). Skin and muscle thickness affect EM signal loss in antennas [31]. The antenna system is strategically placed above the ear region for optimized results for subdural or intra-cerebral bleeding, as shown in Fig.3.

Diverse spherical hemorrhages of varying volumes (radius starting from 0.25 mm to 20 mm) are strategically positioned within the cranial model, specifically in the most probable regions - left and right subdural, and intracerebral areas. This configuration allows for a comprehensive examination of the effects and dynamics of hemorrhages within the framework of the head model.

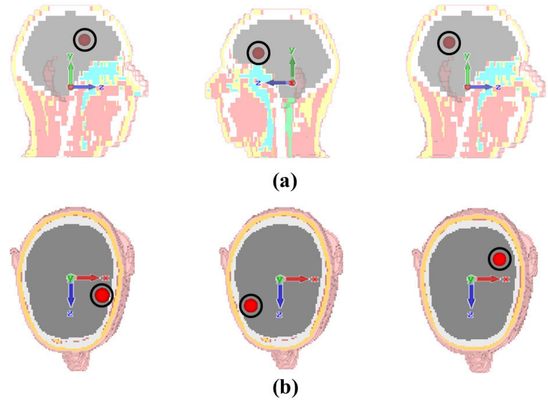


FIGURE 3. Analytical Hemorrhage locations; (a) side and (b)Top view for left subdural, right subdural, and intracerebral hemorrhage (from left to right).

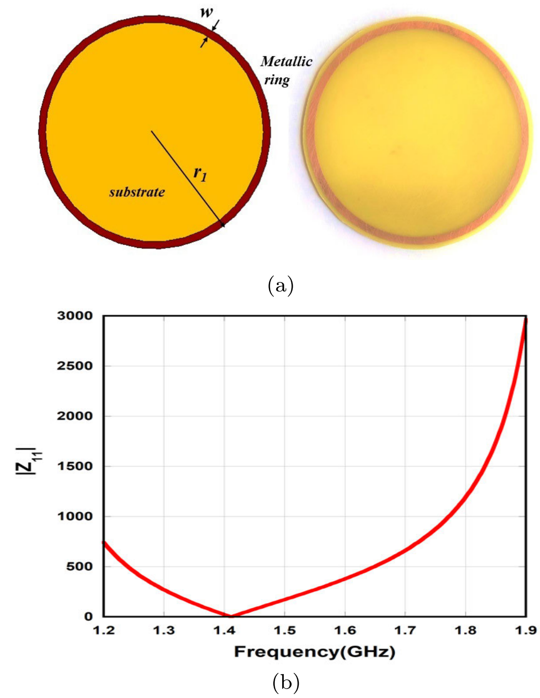


FIGURE 4. RBR reflector: (a)designed and fabricated structure, (b) Simulated surface Impedance Z_{11} parameter.

B. ANTENNA SELECTION

Antennas designed for disease detection must possess essential characteristics, including a directional radiation pattern featuring high gain, a wideband or tunable bandwidth, a compact design for seamless integration, and a low Specific Absorption Rate (SAR) to ensure safety. The directional radiation pattern with high gain enhances the antenna's ability to detect signals accurately, while a wideband or tunable bandwidth allows flexibility in adapting to different human bodies and diverse disease detection scenarios. The compact design facilitates integration into medical devices, and maintaining a low SAR is critical for ensuring the safety of individuals during the detection process. These key properties collectively contribute to the efficacy and safety related to antennas for disease detection. Hence, a bow tie antenna incorporating a resonance-based reflector [34] has been employed for this purpose, leveraging its unidirectional radiation pattern and wide frequency range.

The surface impedances of PEC and PMC can be defined as $Zs \approx 0$ and $Zs \approx \propto$, respectively. Therefore, the reflection phase of the PEC reflector is 180 °, while the PMC reflector's reflection phase is 0 °. The RBR has a reported reflection phase of 0° to 180° in its operating frequency range. It can reflect electromagnetic waves at frequencies higher than the resonance frequency, as it is designed to make the planar antenna unidirectional. An RBR is designed and fabricated, as can be seen in Fig.4, in which the ring's width is denoted by w and the radius of the ring is denoted by r_1. A bow tie

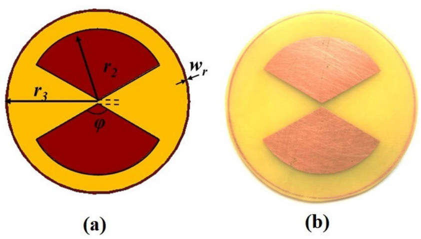


FIGURE 5. Bow tie antenna structure (a) design, (b) fabricated.

TABLE 3. Antenna dimensions.

Parameter	r_1	r_2	r_3	w	w_r	h	h_a	ϕ
Dimension (mm)	33	18.75	26	2	0.1	0.8	13.4	120°

antenna surrounded by a ring is taken since it is unidirectional and can be operated over a wideband frequency range [35] (1.5 GHz-3.17 GHz) covering the ISM Band of 2.45 GHz and optimized to suit the application. The structure is developed on RT Duroid 6002 substrate with a relative permittivity of 2.94 and a thickness of 0.8 mm. The design and dimensions of the antenna are presented in Fig.5 and Table.3; respectively.

Antenna parameter such as the Reflection Coefficient (S_{11}), which is illustrated in Fig.6, depicts the wideband characteristics of the antenna ranging from 1.5 to 3.17 GHz.

Designing antennas for biomedical applications within the GHz range presents numerous advantages when compared to lower frequencies. One notable benefit is the enhanced precision offered by shorter wavelengths at GHz frequencies, resulting in superior resolution in techniques such as radar-based scans and near-field microwave imaging. This improved resolution facilitates detailed visualization of tissues, enabling the identification of potential abnormalities with greater accuracy.

Another advantage lies in the greater tissue penetration achieved by GHz waves compared to lower frequencies. These waves penetrate deeper into the body with reduced attenuation, making them well-suited for applications like brain imaging, and deep tissue hyperthermia treatment. This capability allows for exploring and examining previously inaccessible regions, thereby enhancing diagnostic and treatment capabilities.

Furthermore, utilizing GHz frequencies often necessitates lower power levels to achieve the desired effects, in contrast to lower frequencies. This lower power requirement minimizes heating effects and potential tissue damage, contributing to a safer and more comfortable patient treatment experience.

Additionally, using GHz frequencies offers additional benefits, such as the potential for miniaturization. The smaller wavelengths associated with GHz frequencies allow for the design of compact antennas, a critical factor for developing implantable devices or wearable sensors. This miniaturization potential opens up new possibilities for creating smaller, more discreet biomedical devices without compromising on performance.

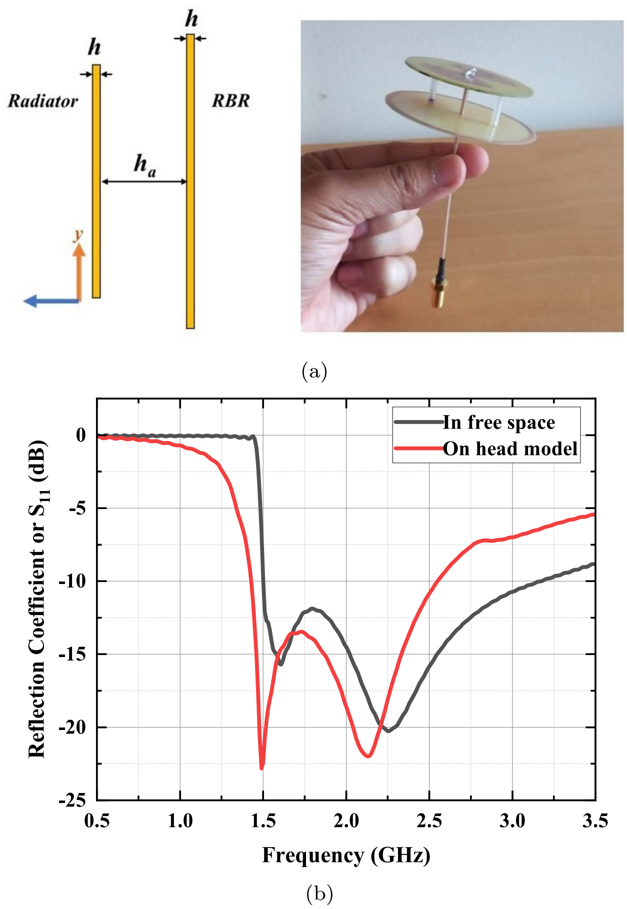


FIGURE 6. (a) Antenna with reflector (designed and fabricated) and (b) simulated reflection Coefficient or S_{11} for antenna placed in free space and on head model.

In addition, the frequency range encompasses the 2.4 GHz ISM band. The unidirectional radiation pattern with a good peak gain of the incorporated antenna encourages penetration inside the head. Radiation characteristics of antenna in free space are presented in Fig. 7.

C. COUPLING ANALYSIS

The examination of antenna coupling holds significant importance in electromagnetic design and the optimization of communication systems. This process entails investigating and assessing interactions between antennas, and analyzing the potential impact of their proximity and electromagnetic fields on each other's performance.

We conducted an analysis to assess the coupling between the transmitting and receiving antennas in our proposed wearable antenna system. The coupling coefficient data is visually represented in Fig. 8, illustrating the relationship between the antennas in this study.

D. ANTENNA PLACEMENT AND FIELD ANALYSIS

To achieve optimal data collection and hemorrhage detection, a pair of antennas are placed above each ear in the frontal region of the head (5 mm gap from the head surface). The

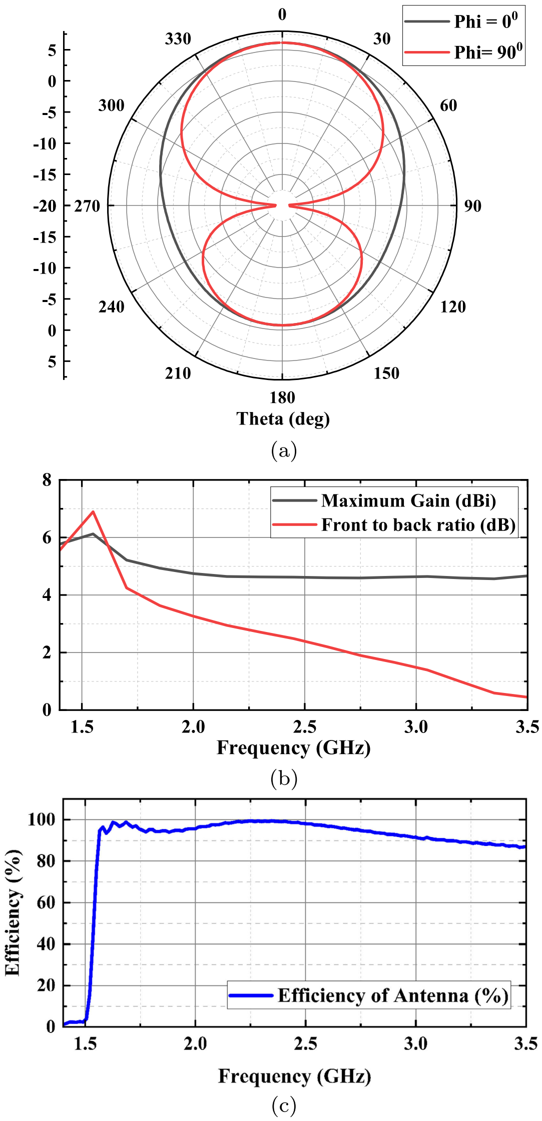


FIGURE 7. Simulated radiation characteristics: (a) Radiation pattern of antenna at 1.66 GHz, (b) gain and front-to-back ratio (FBR) plot, and (c) efficiency of antenna.

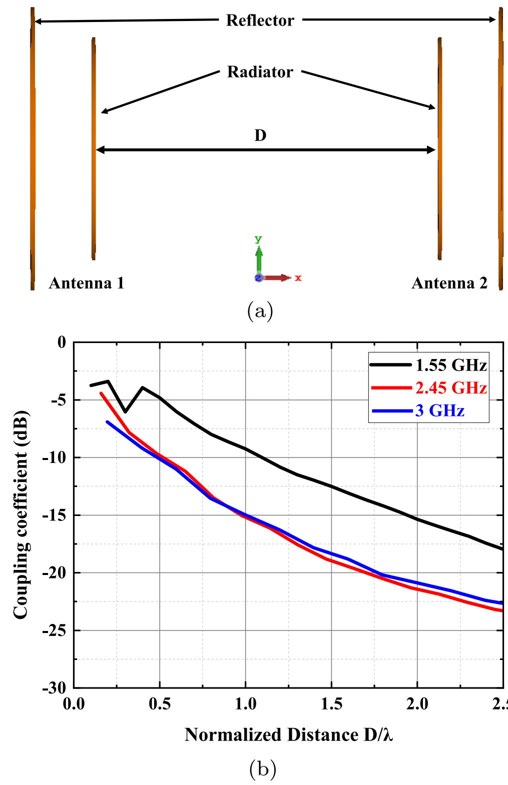


FIGURE 8. Simulated coupling analysis between antennas: (a) setup and (b) coupling coefficient plot vs normalized distance.

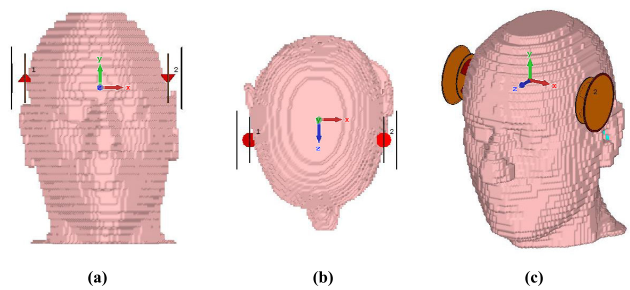


FIGURE 9. Antenna placement: (a) Front view (b) Top view (c) Isometric view.

antennas are diametrically opposite and arranged linearly to cover the entire brain, including subdural and intracerebral spaces. Positioning the antennas above the ears on the head model induces a shift in resonance frequency while minimally impacting the overall operating bandwidth. Consequently, the antenna has been calibrated to operate within the specified frequency range, ensuring effective signal penetration for hemorrhage detection.

This section outlines the near-field analysis, which primarily examines the E field, H field, EM wave penetration, and SAR within the Gustav head model. The antenna's performance is evaluated by analyzing the EM signal's ability to penetrate head tissues. Fig. 10 depicts the E-field and H-field distribution in the Y-Z plane at a frequency of 2.26 GHz. It has been seen that the antenna remains directional towards the model and the EM wave can penetrate the head tissues.

Specific Absorption Rate (SAR) is the rate at which the human body absorbs electromagnetic energy from EM fields. It assesses potential health risks related to exposure from microwave radiation on the brain when it penetrates the skull. The SAR analysis is essential in considering brain modalities for microwave applications to ensure patient safety. The SAR value is determined by the following equation [36].

$$SAR = \frac{|E|^2 \times \sigma}{M}$$

where E stands for the electric field, M for the mass density, and σ for the tissue conductivity in the human head model. The IEEE radiation exposure standard mandates a maximum SAR value of less than 1.6 W/kg [37]. In this study, 1 mW of input power is supplied to the antenna, and the SAR

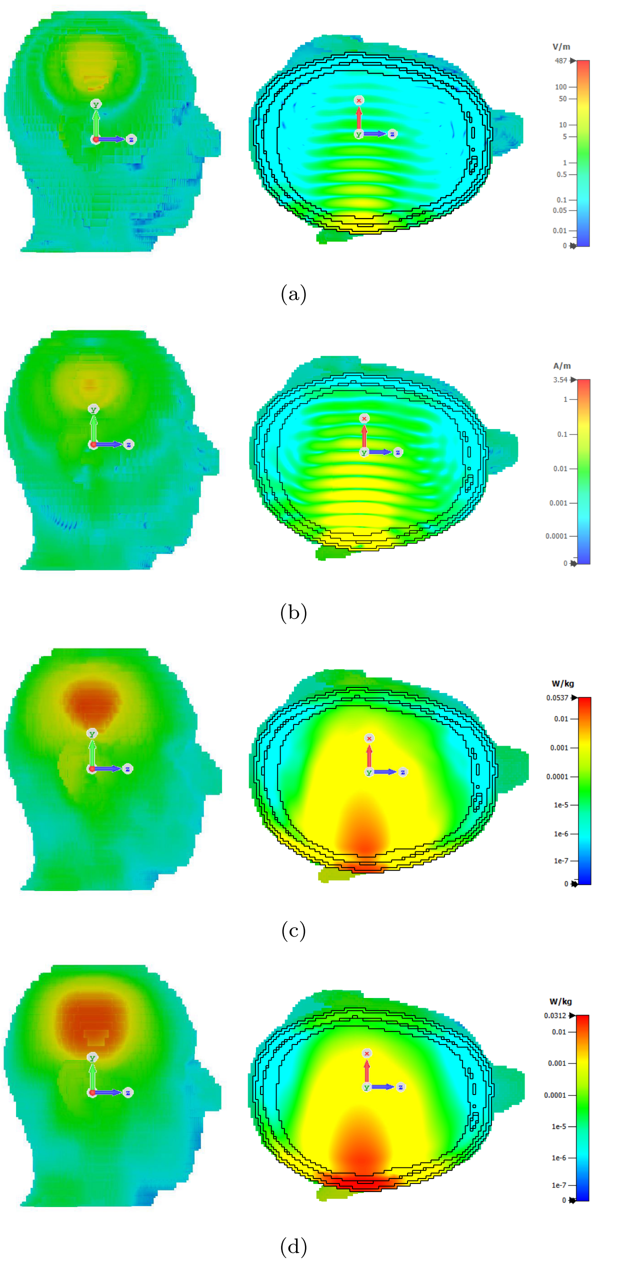


FIGURE 10. (a) E-field and (b) H-field distribution; and Specific Absorption Rate (SAR) distribution for (c) 1 gm average mass and (d) 10 gm average mass at 2.26 GHz with 1mW input power.

calculated for 1 gm and 10 gm of average mass at 2.26 GHz, is as shown in Fig.10.

E. COLLECTION OF DATA

Simulated scattering parameters are collected and processed to detect the type of hemorrhage. S_{21} is the forward transmission coefficient that describes the amplitude, intensity, or total power of a wave as it travels from the transmitter to the receiver. This parameter is influenced by the medium (i.e., head model) between the two antennas, which affects the power transfer from one antenna to the other antenna. The head model consists of layers such as skin, fat, bone,

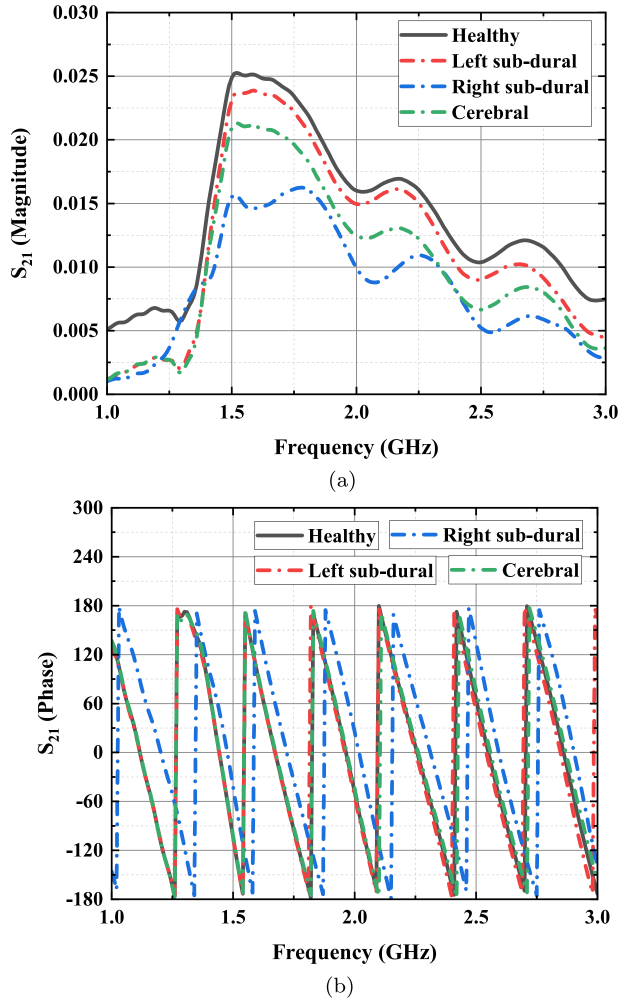


FIGURE 11. Simulated transmission coefficient(S_{21}) (a) magnitude and (b) phase plot for healthy condition and hemorrhages of the radius of analytical bleeding = 10 mm.

and brain, which act as intermediary mediums. In the process of gathering simulated data, the transmission coefficient S_{21}, both in terms of its magnitude and phase, is recorded distinctly for each type of hemorrhage. The radius of the analytical bleeding sphere is varied parametrically from 0.25 mm to 20 mm with a step size of 0.25 mm for different stages of the disease, ranging from early stages to severe cases. For intra-cerebral hemorrhage, a spherical bleeding object is inserted in the central back space of the brain, and a total of 80 variations of transmission coefficient (S_{21}) are gathered, including 79 variations for different stages of the disease and 1 for healthy, and are forwarded for further investigation. Similarly, data collection for the other two hemorrhage spaces has been done. Transmission coefficients are plotted in (Fig.11) against 1000 frequency points in the frequency range of 1 to 3 GHz.

III. MACHINE LEARNING IN MICROWAVE SYSTEMS

Antenna-based microwave imaging (MWI) is an innovative method that offers a cost-effective and non-invasive approach to medical diagnosis and treatment. By utilizing electromagnetic waves in the microwave frequency range, MWI can examine the dielectric properties of biological tissues, which can provide valuable information about their overall health. One of the many applications of MWI is the detection of conditions such as breast tumors, stroke, brain injuries, skin diseases, and other ailments.

Nonetheless, MWI faces several obstacles, including low resolution, complexity, noise, and artifacts. To address these issues, machine learning (ML) can be implemented to enhance the precision and efficiency of MWI systems. By analyzing microwave signals or images gathered by MWI systems, ML can identify significant features or patterns that aid in diagnosing diseases. In recent times, several research works have been reported where ML is successfully integrated with MWI systems.

The authors of a recent study [38] aimed to develop an improved predictive model for diseases. The study collected data on 5145 cases and investigated 39 diseases using 86 attributes from various datasets. The study used machine learning algorithms, including light gradient boosting machine and extreme gradient boosting, along with a deep neural network to create an ensemble model that achieved high prediction accuracy and F1-score for the five most common diseases. The study analyzed feature importance using the confusion matrix and SHAP value methods.

Another study [39] describes a machine learning-based system for breast lesion detection using microwave ultra-wideband devices. The system utilizes several machine learning algorithms, including nearest neighbor, MLP neural network, and support vector machine, to create an intelligent classification system. The study shows that the support vector machine with a quadratic kernel can classify breast data with 98% accuracy.

In a new report [40], researchers have developed a fully textile antenna-based sensor system for detecting breast tumors. The proposed system utilizes machine learning algorithms to differentiate between malignant and benign breast tissues, achieving a 100% classification accuracy on tested datasets. The sensor is compact and made entirely of textiles, fitting comfortably on the breast.

Lastly, a recent study [41] proposes a fast and accurate machine-learning algorithm to predict breast lesions using microwave signals. The study shows that the support vector machine algorithm with a third-degree polynomial kernel achieves 99.7% accuracy, outperforming conventional binary classification algorithms. This method could assist radiologists in detecting tumors accurately and early. The study highlights that microwave imaging is a safe and non-ionizing screening method for breast cancer detection.

IV. PROPOSED MACHINE LEARNING FRAMEWORK

In the current study, the S-parameter data obtained from the proposed two-antenna system is used to train various

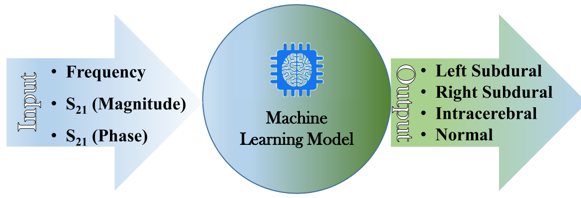


FIGURE 12. Proposed Machine Learning framework. Input features to the machine learning models are 'Frequency', 'Angle (S_{21})' and 'Magnitude (S_{21})'. The output is the position of the brain hemorrhage i.e. 'Left', 'Right', 'Central Back' or 'Normal'.

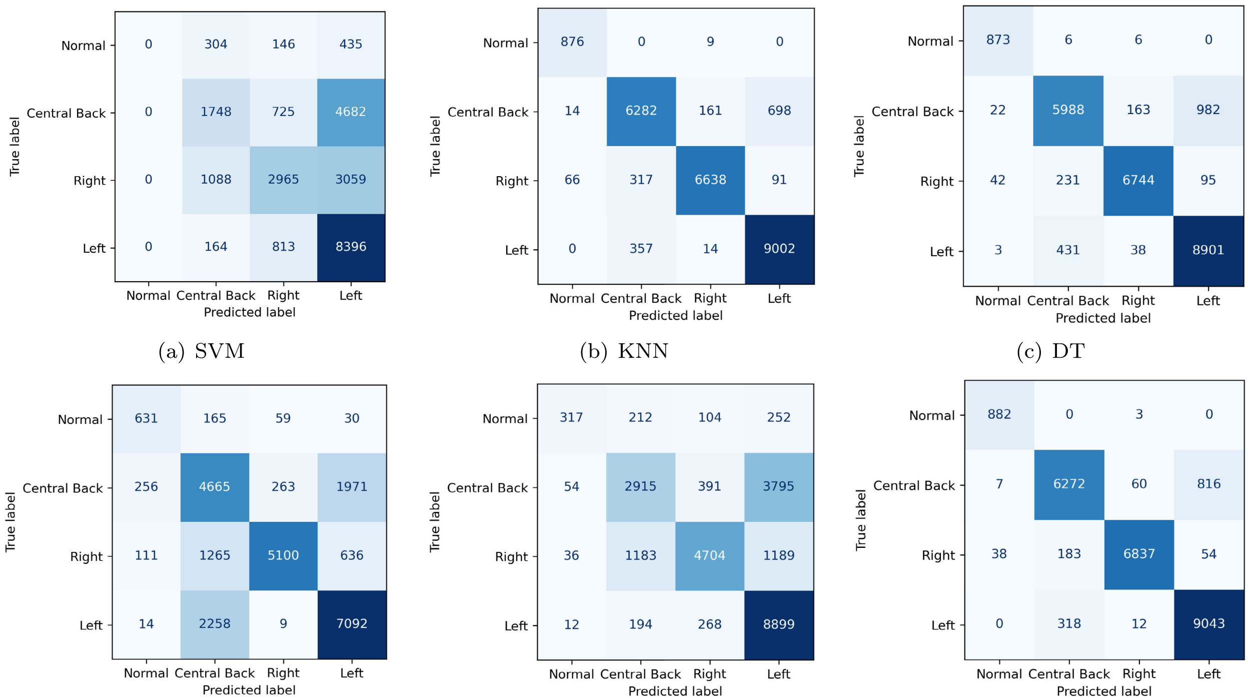
machine learning models to predict the position of brain hemorrhage inside a human subject. Specifically, the input to the machine learning models is 'Frequency', 'Angle (S_{21})', and 'Magnitude (S_{21})' which are extracted from 'S_{21}' parameters obtained from the proposed antenna system. The model attempts to predict the position of the hemorrhage inside the human brain. The positions considered in the current study are 'Left', 'Right', and 'Central Back'. In case of no hemorrhage, the model classifies the input data to the 'Normal' class. Thus, the input to the machine learning models is a 3-dimensional vector. Now, to solve such classification problems where the data samples are structured, machine learning models that are used in the current study are some of the most suitable ones. The framework outline is depicted in Figure 12.

A. MACHINE LEARNING CLASSIFIERS

The Support Vector Machine (SVM) is a classification algorithm that identifies a hyperplane in the feature space to segregate classes with maximum margin. In the given set of training data $(x_1, y_1), \ldots, (x_n, y_n)$, where x_i denotes the ith data point and $y_i \in -1, 1$ is its corresponding label, SVM resolves an optimization problem, with the objective of minimizing $\frac{1}{2}|w|^2$, subject to the constraint that $y_i(w \cdot x_i + b) \geq 1, i = 1, 2, \ldots, n$. Here, $|w|$ represents the weight vector's norm. The hyperplane equation is $w \cdot x + b = 0$, where w denotes the weight vector, b is the bias, and $\cdot$ denotes the dot product. By utilizing various kernel types, including linear, polynomial, and radial basis function (RBF) kernels, SVM can handle both linear and nonlinear data.

Multilayer Perceptron (MLP) is a neural network architecture that includes several interconnected layers of nodes or neurons. During training on a given set of data $(x_1, y_1), \ldots, (x_n, y_n)$, MLP can be viewed as a function $f(x; \theta)$ that maps input x to output y. The parameters θ are learned from the training data by minimizing a loss function $L(y, f(x; \theta))$. The output of a neuron in MLP is determined by the weighted sum of its inputs plus a bias, which is then transformed by the activation function to introduce nonlinearity into the model.

The output of MLP is obtained by applying the softmax function to the weighted sum of the first hidden layer outputs using the weight matrix $W^{(2)}$ and bias vector $b^{(2)}$ of the output layer. The first hidden layer output $h^{(1)}$ is computed from the input data x using the same process as



(d) MLP (e) GB (f) RF

FIGURE 13. Test phase Confusion Matrices of different classifiers used in the current study.

the output layer but with different weight matrices and bias vectors.

The Decision Tree (DT) algorithm is widely used for classification tasks. DT constructs a tree-like model that makes decisions based on the features of the data. It learns a set of if-then rules, represented as a tree, where each node corresponds to a test on a feature and each branch corresponds to the outcome of the test. The leaves of the tree represent the class labels. DT recursively builds the tree by selecting the feature that provides the most useful information about the target variable. The usefulness of a feature is determined using the entropy or the Gini index, which quantifies the impurity of a set of data.

KNN is an easy-to-understand classification algorithm that relies on similarity. When presented with a new data point, KNN identifies the K most similar data points in the training set and uses the majority class among them to classify the new point. To achieve this, KNN uses the Euclidean distance to measure the distance between two data points. The Euclidean distance formula is a way to calculate the distance between two points in a multi-dimensional space. It calculates the square root of the sum of the squared differences between each feature of the two points.

Gradient Boosting (GB) is an ensemble learning technique that combines multiple weak models to create a stronger model. It constructs the model in stages, with each subsequent model attempting to fix the errors of the previous model. The ultimate model is a weighted combination of the individual models. Given a training dataset $(x_1, y_1), \ldots, (x_n, y_n)$, GB minimizes a differentiable loss function $L(y, f(x))$ to predict the label $f(x)$ from the true label y. The loss function is often the mean squared error or the log loss. The model is built in stages, with each subsequent model minimizing the loss function of the residual errors from the previous model. The final model is a weighted sum of the individual models, and the weights are determined by the performance of each model on the validation set.

B. PARAMETRIC SETUP

The classifiers used in the current study are implemented using the Python based scikit-learn library [42]. For SVM, a linear kernel with a C value of 1.0 is used. For MLP, a three-layered network with a ReLU activation function and 100 hidden neurons with a learning rate of 0.001 is used. The decision tree is constructed using the Gini impurity criterion and set to a maximum depth of None. For KNN, the number of neighbors is set to 5. GB uses 100 trees with a learning rate of 0.1, while random forest is trained with 100 trees and a maximum depth of None. All classifiers are implemented using default settings provided by scikit-learn.

To assess classifier performance, several metrics are used, such as accuracy, precision, and recall. Accuracy is the proportion of correctly classified instances, while precision is the proportion of true positive predictions out of all positive predictions, and recall is the proportion of true positive

TABLE 4. Performance of machine learning-based prediction for brain hemorrhage.

Test Data	Frequency (GHz)	S_{21} (Magnitude)	S_{21} (Phase)	Hemorrhage (Target)	Hemorrhage (Predicted)
1	2.11	0.005994	-123.398465	Right	Right
2	2.54	0.009638	-2.420771	Left	Left
3	3	0.003521	-168.993605	Central Back	Central Back
4	2.41	0.003549	57.453285	Central Back	Central Back
5	2.88	0.005405	-5.906295	Central Back	Central Back

TABLE 5. Performance comparison of machine learning models to predict brain hemorrhage using two antenna system.

	Accuracy	Precision	Recall
SVM	53	72	53
MLP	71	71	71
DT	92	92	92
KNN	93	93	93
GB	69	78	69
RF	94	94	94

predictions out of all actual positive instances. These metrics are calculated using the following formulas:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{TP + FN}$$

Here, TP refers to the number of true positive predictions, TN refers to the number of true negative predictions, FP refers to the number of false positive predictions, and FN refers to the number of false negative predictions. To prevent overfitting, the dataset is split into training and testing sets using the held-out method, with 70% of the data for training and 30% for testing. This process is repeated ten times to ensure the results' reliability.

C. PERFORMANCE COMPARISON AND ANALYSIS

The test phase confusion matrices of different classifiers used in the current study are reported in Figure 13 and the results are presented in Table 4. The accuracy of the classifiers varied greatly, with Decision Tree and Random Forest showing the highest accuracy of 92% and 94%, respectively. K-Nearest Neighbors (KNN) also showed good performance with an accuracy of 93%. The Support Vector Machine (SVM) and Gradient Boosting (GB) performed relatively poorly with an accuracy of 53% and 68%, respectively.

Looking at the precision and recall values, Decision Tree, KNN, and Random Forest all showed 93-94% precision and recall, indicating that they have good performance in correctly identifying both positive and negative cases. MLP also showed consistent precision, recall, and accuracy scores of 73%. In contrast, SVM and GB showed lower precision and recall scores, indicating that they struggled to correctly identify positive cases. In Table 5, a few randomly selected test samples are shown along with predicted values obtained from the best-performing classifier i.e. Random Forest (RF).

Overall, the results suggest that Decision Tree, KNN, and Random Forest are the best classifiers in the current study for this particular dataset, as they showed high accuracy, precision, and recall values. The low performance of SVM and GB can be attributed to the fact that they may not be well-suited for this case.

V. CONCLUSION AND FUTURE SCOPE

In this study, a two-antenna system utilizing Machine Learning classifier models has been presented for the non-invasive detection of Brain Hemorrhage. The system comprises directional bow-tie antennas with adequate gain, placed around a human head model to provide information about the presence and type of Hemorrhage. Scattering parameters were obtained from a simulated system comprising the Head model, Hemorrhage at three distinct sites, and the antennas placed at various positions over the head model. The data were processed by several categories of classifiers to generate a result indicating the type of hemorrhage. The study evaluated the performance of the classifiers using accuracy, precision, and recall, which demonstrated that Decision Tree, KNN, and Random Forest were the most appropriate classifiers for diagnosing Brain Hemorrhage. The results of this study show that the antenna system implemented with ML classifiers is highly efficient and effective in diagnosing Brain Hemorrhage. However, the study suggests that future approaches should collect a large amount of training and testing data from diverse body models available in simulation environments, phantom measurements, and real-time human trials to improve the system's performance and its ability to diagnose Hemorrhage at any site inside the human head.

To conclude, the two-antenna system presented in this study, integrated with Machine Learning Classifier models, provides a cost-effective and non-invasive method for diagnosing Brain Hemorrhage. The system's accuracy, precision, and recall demonstrate its potential for use in clinics and monitoring systems.

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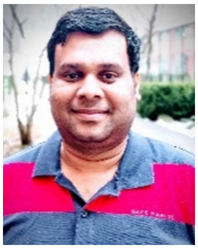

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