



Machine learning enabled smart non-invasive glucose monitoring system using RF sensors

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ABSTRACT

This study presents a non-invasive blood glucose monitoring system that integrates an RF-based biosensor with machine learning techniques for enhanced accuracy and reliability. The sensor utilizes an Octagonal- Shaped Complementary Split Ring Resonator (OSCSRR) arranged in a honeycomb structure, operating at a resonance frequency of 2.45 GHz. Blood glucose levels ranging from 0 to 300 mg/dL were analyzed using the Cole-Cole model to determine variations in the reflection coefficient (S11). The sensor was fabricated on a Rogers RO4003C substrate and validated using a Keysight N5227A Microwave Network Analyzer, with a measured return loss deviation of 5 dB from simulated results. Machine learning algorithms, including Singular Value Decomposition (SVD), were employed to process dielectric characterization data and enhance the sensitivity in detecting glucose concentration variations. The trained model effectively distinguished glucose levels by identifying subtle changes in electromagnetic responses. The proposed approach demonstrates significant potential for non-invasive glucose monitoring, reducing patient discomfort while ensuring high sensitivity and accuracy.

1. Introduction

Nowadays, diabetes is a widespread metabolic disorder that significantly impacts public health. A metabolic disorder that refers as diabetes, it occurs in human body due to an increase the sugar level in blood. In order to control blood sugar levels, the pancreas secretes insulin. Insulin production from the pancreas is the basis for the classification of Type 1 and Type 2 diabetes. The type 2 is more prevalent in today's population. A glucometer and blood test were previously used to determine the blood glucose level. Intrusive blood pricking is necessary for measuring blood glucose in these types of tests. The emergence of less invasive continuous glucose monitoring devices has improved the

lives of diabetic patients in recent years, but it has drawbacks as well, such as uncomfortable insertions, high costs, and discomfort. For those with diabetes, controlling blood glucose levels effectively is essential to avoiding major side effects such renal failure, heart attack, stroke, and amputation of a lower limb. However, the majority of glucose monitoring devices now on the market need finger pricking, which can be costly and painful for users. As a result, there is a growing need for non-invasive, painless biosensors for glucose monitoring. Microwave-based methods have proven over time to be effective in characterizing biological tissues, measuring variations in blood glucose levels in the finger, and developing sensitive sensors that are useful for diabetics. Furthermore, biological tissues can be readily penetrated by microwaves

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without endangering the health of the user [1–5]. Differential Continuous Wave Photo Acoustic Spectroscopy (DCW-PAS) enables non-invasive blood glucose monitoring in both *in vitro* and *in vivo* settings. Amplitude modulation combined with two different light wavelengths is how the DCW-PAS method determines the concentration of glucose in an object. The results of invasive blood glucose sensor assessments of oral glucose tolerance tests (OGTTs) conducted on healthy individuals are included in the study together with the DCW-PAS evaluations. Good connection has been found between the blood glucose level estimated by invasive sensors and photo-acoustic signal. Silicon nitride (Si₃N₄) substrate, gold film, and barium flint glass are the materials used to make the plasmonic sensor used to test blood glucose levels. On normal incidence, the plasmonic sensor rejects infrared wavelengths due to the resonance between the incident plane wave and the plasmonic wave. The effect of ambient refraction or glucose concentration on the plasmonic structure's sensitivity to blood glucose [6]. Spoof Surface Plasmon Polariton (SSPP) end fire sensor measures on-body glucose and keeps track of aqueous glucose solutions. With a small effective aperture, the glucose water solution receives the end fire beam radiation from the SSPP end fire sensor. By suppressing the side lobes, a set of triangular ground planes at the sensor's CPW port limits the amount of glucose that can be sensed. Greater sensitivity in measuring glucose concentrations is made possible by the slow wave characteristic of the SSPP end fire sensor [7,8].

The glucose response, which is characterized by low Radio Frequency (RF) emissions, can be effectively used to diagnose diabetes patients. The impedance analyzer is used to determine the conductivity and permittivity ratios of aqueous solutions at various glucose concentrations ranging from 1 KHz and 1 MHz. Additionally, the bio-impedance to be measured from the forearm during the cardiac cycle is used by the blood impedance measure for glucose monitoring, which employs a polygraph at 1000 Hz. The cardiac cycle is evaluated by the variation in bioimpedance. The interaction between blood glucose concentration and bioimpedance is assessed in order to remove the effect of tissue [9]. Three different microwave resonator configurations meet the requirements to evaluate the blood glucose level.

The construction of the microwave resonator is placed on the patient's finger. The size and form of the finger should match the resonator. The structure's resonance frequency and the tissue's dielectric characteristics are altered by variations in blood glucose levels [10]. Lab-made duplicate blood samples with different glucose content levels are detected by a combined millimeter wave radar system. Diabetes patients' blood glucose is non-invasively monitored by the millimeter-wave radar. Using a discrete time Fourier transform, the mm-wave radar signal can detect different glucose concentrations in samples of hemoglobin [11]. Blood glucose concentration is non-invasively measured using near-infrared spectroscopy. Blood glucose concentration is measured using the infrared light pass-through finger and absorbance is calculated using Beer-Lambert law. Finger thickness and blood glucose level are correlated with infrared absorption [12]. A very sensitive glucose fringe field Microstrip Line (MLIN) using glucose as the substrate and Material under Test (MUT) detects glucose concentration and ports. MUT and the MLIN electromagnetic field interact, causing fluctuation in S₁₁ min. The bin correlation algorithm is used to estimate glucose concentrations using single variate, multivariate, and multivariate estimation methods [13–15].

Long-term subcutaneous tissue glucose monitoring in diabetic patients is facilitated by an implanted sensor equipped with a telemetry system. The implanted sensor consists of an electrochemical oxygen detection and telemetry system connected for wireless data transfer, catalase, immobilized glucose oxidase membrane, and polydimethylsiloxane membrane [16]. A Complementary Split Ring Resonators (CSRR) with hexagonal shapes that replicate a honey-cell pattern are present in the sensor element. The planar micro strip with dielectric substrate was attached to the resonator. The CSRRs were linked by means of microstrip transmission line to a 2.4–2.5 GHz radar system.

The combination sensor device detects blood glucose levels with good sensitivity, as it dissolves in the blood similarly to aqueous solutions [17].

The SIW (Substrate Integrate waveguide) planar sensor uses the slots in the top conductor of the sensor and the interdigital arms to generate a notable and confined field increase within the sensing area. Furthermore, fingertip is used as material under test (MUT) and analysis is done on the impacts of finger displacement and prints [18]. Blood glucose is monitored via an ultrasonic piezoelectric Micro Electronics Mechanical Systems (MEMS) receiver based on zinc oxide. Pressure and stress are converted into voltage on the ultrasonic piezoelectric MEMS receiver's surface and radial displacement.

The voltage changes in relation to the degree of blood concentration. A good connection between the glucometer reading and the simulation analysis of the glucose data was seen [19]. The RF sensor uses blood dielectric changes to measure blood glucose levels. The sensor frequency shifts below 8 MHz as a result of the dielectric change brought on by glucose. Additionally, the blood layer, skin, fat, pressure, and finger posture all cause frequency shifts [19]. A complete blood sample is obtained from a minor skin wound using a novel micro-actuator based on shape memory alloy (SMA) microsystem design. It monitors the blood glucose level directly from the blood sample [20].

An implanted electrochemical sensor device with wireless power allows for continuous blood glucose monitoring. The RFID sensor system is directly powered, controlled, and configured by a high-frequency (HF) external reader. The off-chip support circuitry requires a glucose microsensor in addition to a tuned antenna [21]. The study explores the development of a broadband terahertz antenna incorporating a complementary ring-resonator design for next-generation 6G applications. It emphasizes the antenna's performance and potential for advanced communication systems [22–24].

This work deals with the development of a hexagonal Split Ring Resonator sensor for the accurate characterization of the permittivity of organic liquids. Before its fabrication on an FR4 substrate, the 30 × 22 × 1.6 mm compact antenna has been simulated with the accent of differential sensing through resonance at a frequency of 5.3 GHz, resulting in extraordinary capabilities in capturing the complex permittivity profiles of unknown liquid samples [25]. In this context, a TRB-CSRR has been proposed to be applied in the measurement of the sensitivity and thickness of various dielectric materials.

The designed antenna is fabricated on a Roger RO4350 substrate and measures 20 × 20 × 0.8 mm³. The working frequency is 4.86 GHz, and it has outstandingly good field confinement. The accuracy of the permittivity and thickness in the solid dielectric setting has been greatly enhanced [26]. This work fabricates a CSRR device aiming to measure the resonance properties and the sensitivity of the materials. This device resonates at 2.5 GHz with a quality factor of 520 and 7.321 MHz/er sensitivity. Therefore, in the current study, the influence of MUT thickness over the resonance has been fully investigated under two different conditions: using and not using ST for scanning the edge, as shown below. This shows that the CSRR is able to identify even a very minute change in material properties [27]. This paper reports on the analysis of a curve-fed complementary split ring resonator (CSRR) with the defected ground structure (DGS) for sensing applications in the detection of semi-solid material. This proposed design, at 2.5 GHz, shows a Q-factor of 520 and high sensitivity of 1.072. The study focuses on the efficacy of the antenna in identifying and analyzing semi-solid materials, highlighting its huge potential for practical sensing applications [28].

CSRR is designed for solid material characterization and it is fabricated with a 20x25x1.52 mm* size using Roger RT/Duroid 6002 substrates and simulated using HFSS microwave studio. It operates at a resonant frequency of 2.5 GHz, showing a Q-factor of 520 and is highly sensitive, with values of 4.806 and 4.773 for Di-water and Turmeric samples, respectively. Such a work could be critical for realizing the effectiveness of CSRR in the characterization of solid materials and,

therefore, establishing it as one of the strong tools for material detail analysis [29,30]. Software-Defined Radio is proposed as an inexpensive alternative to the usually very expensive Vector Network Analyzer in dielectric property measurements. Two approaches have been investigated: the cavity perturbation technique using a cylindrical resonator at a frequency of 2.5 GHz and the Complementary Split Ring Resonator operating at 1.25 GHz. Both methods have been found successful in measuring dielectric constants and loss tangents with SDR acting as a scalar network analyzer. The measured results prove the possibility of the SDR capability in providing close measurement accuracy with that available in a VNA. In dielectric material studies, it becomes flexible, inexpensive RF measurement equipment [31].

In the existing work, biomedical sensor antennas have either large

size, low sensitivity and also high cost. In order to overcome this, RF based sensor is proposed for non-invasive blood glucose level measurements. The sensor is composed of four Octagonal Shaped Complementary Split-ring Resonators arranged in a honeycomb structure and sensing elements are coupled via a micro strip-line fed by a 50 Ω for ISM band applications. The proposed honeycomb OSCSRR have a resonance response of about -25 dB which makes more sensitive to glucose samples at the level of interest. The work involves designing and 3D electromagnetic simulations of the microwave sensor with a human fingertip implanted in the detecting zone and compares them with preliminary observations. The thickness of various finger layers, including skin, fat, blood, and bone, with their corresponding dielectric characteristics, were also evaluated in the study in relation to the

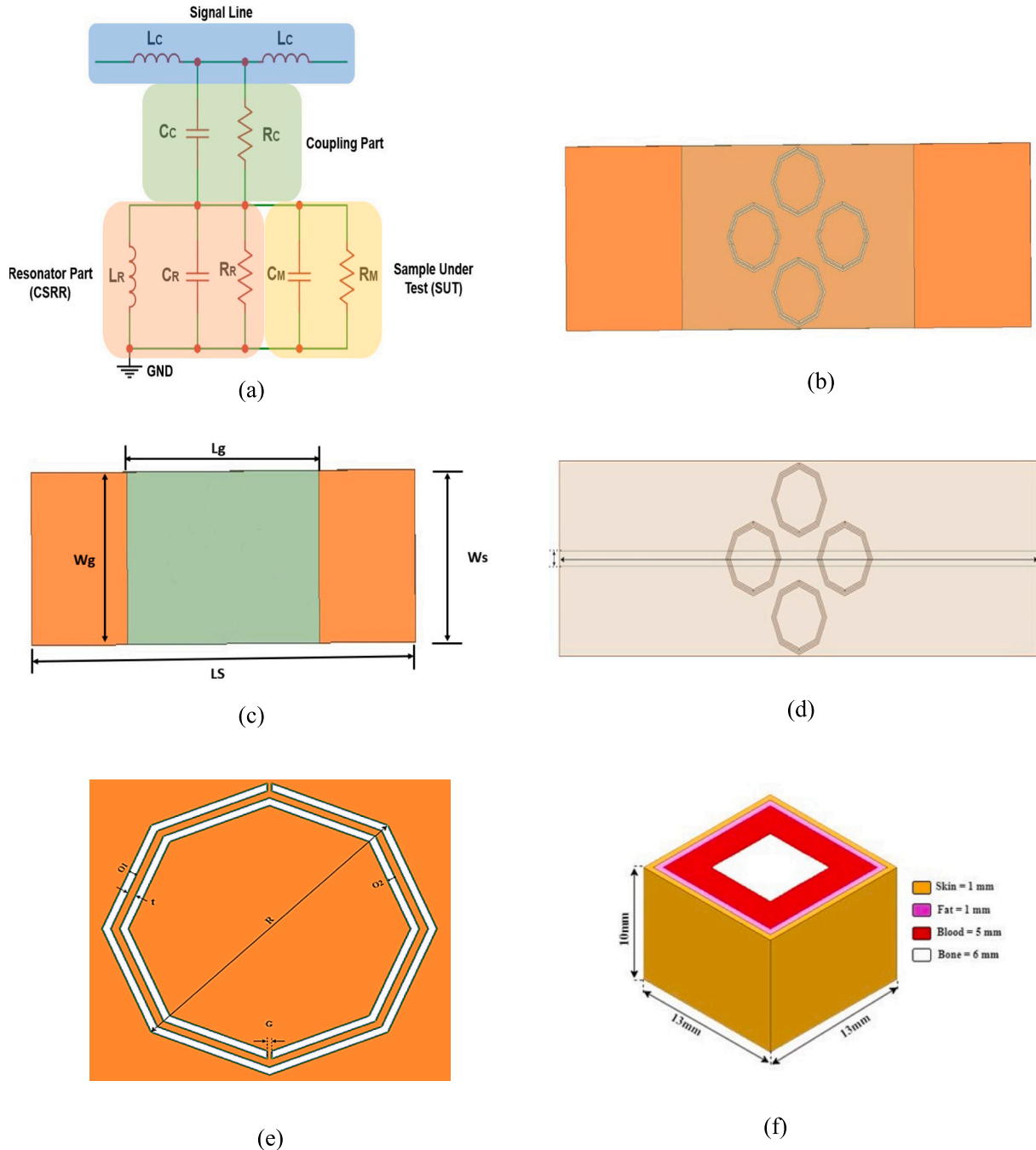


Fig. 1. (a) CSRR sensor model equivalent circuit under testing conditions, (b) Four Octagonal – Shaped Complimentary Split Ring Resonator, (c) Octagonal Shaped CSRR with testing glass, (d) 50 Ω Microstrip feeding line, (e) Single Element of OSCSRR, and (f) 3D figure model with thickness of layers.

microwave sensor. ANSYS HFSS Software simulations are used to illustrate the design. The key factor influencing variations in blood's dielectric characteristics is the content of glucose. The objective of the study is to measure the variations in resonant frequency magnitude brought on by variations in glucose levels by putting the finger on the resonator [32–34].

This article presents an RF-based biosensor using an Octagonal Complementary Split Ring Resonator (OSCSRR) for non-invasive glucose monitoring, integrating machine learning (ML) for improved accuracy. Section 2 covers the sensing mechanism, sensor design, and a human finger model, with ML refining signal processing and predictions. Section 3 analyzes results, exploring the sensor's electromagnetic responses and glucose level variations, leveraging Singular Value Decomposition (SVD) and ML for feature extraction and predictive modeling. Section 4 validates the findings through simulations and experiments. Finally, Section 5 highlights the sensor's effectiveness and ML's role in advancing non-invasive glucose monitoring.

2. Proposed system

2.1. Glucose sensing mechanism

Microwaves and matter are interacting in a variety of ways, and to understand this interface we have developed various methods to study it. These methods can be classified as follows: resonances, transmission lines and free space. Dielectric materials interact with electromagnetic fields to change resonant sensor characteristics, including quality factor, bandwidth and resonant frequency. A complex relative permittivity can be used to describe the interactions between biological tissue and electromagnetic fields.

The physical behavior of the integrated complementary split-ring resonator (CSRR) as used in glucose sensing, we used a simple lumped element model of the OSCSRR that describes the lumped elements. There are three parts in this electrical model, as shown in the Fig. 1. In order to simulate the magnetic coupling that results from the signal line crossing the OSCSRR structure, an inductance LC is used to model the signal line (with 1.5 mm width) that is used to excite the resonator. Second is the dielectric substrate, which serves as an electrical interface between the signal line and the resonators in the ground plane (intermediate junction measuring 66 mm long, 20 mm wide, and 0.8 mm thick).

The dielectric losses on the substrate as well as the conductive losses on the metal strip can be approximated by a series capacitor CC and a resistance RC. One of the final components is an octagonal four cells resonator modeled as a parallel resonant circuit of RLC with the inductance LR being determined by the windings of the dielectric rings within each octagonal cell. A parallel capacitance CR is created by spaces t between rings, metallic gaps g and a resistance RR is used to represent dielectric and conductive losses. Fig. 1 (a) shows the CSRR sensor model equivalent circuit under testing conditions.

The sensor's resonance behavior can be modeled by considering the energy stored in the inductive and capacitive components of the CSRR structure. When excited by an incident electromagnetic wave, the resonator stores electric and magnetic energy, and resonates when these energies are balanced. This behavior is observed as a dip in the reflection coefficient S11, with the resonant frequency (Eq.1) and bandwidth (Eq.2) defined by:

$$f_R = \frac{1}{2\pi\sqrt{LC}} \quad (1)$$

$$Q = \frac{f_R}{\Delta f_{3dB}} \quad (2)$$

where f_R is the resonance frequency, Δf_{3dB} is the 3 dB bandwidth, and Q is the loaded quality factor of the sensor. Changes in the dielectric

properties of the material under test (e.g., glucose solution) perturb the effective capacitance C , causing measurable shifts in f_R and S11, which form the basis for glucose level detection. The relationship between the effective capacitance C_M and the sample's relative permittivity ϵ_r is well-established, while the effective resistance R_M correlates with dielectric losses and is more complex to model precisely. Upon excitation, the CSRRs store electric and magnetic energy within their patterned slots, which behave as lumped inductive and capacitive elements.

In this formula, Δf_{3dB} denotes the resonance peak's bandwidth of 3 dB. $C_e \sim C_R \parallel C_M$ denotes a function of glucose sample concentration; this quantity represents the effective capacitance of the CSRRs integrated. CSRR and loaded glucose sample dielectric losses are symbolized by R_P , the equivalent resistance obtained by parallelizing R_c with R_e .

The stored electric energy as well as the magnetic field that are concentrated in the CSRRs region interact with glucose samples placed near the CSRRs, even though the magnetic field is confined between the slit traces. The perturbation of the CSRR effective capacitance C_e as a result of the change in dielectric permittivity of the loaded glucose samples would reflect in f_R . A constant volume sample glucose concentration is thus determined by this shift in the resonance frequency. Likewise, the variability in amplitude of the resonance profile can be attributed to the loss property of glucose.

Through careful analysis of the modified resonance behavior, it is possible to correlate the modified resonance attributes directly with the corresponding glucose levels. The CSRR sensor under loading conditions is illustrated in Fig. 1(a). In order to understand in what way changes in biological tissues, such as blood and skin, affect the performance of the sensor, this model is essential. A sensing region was simulated with different glucose concentrations between 0 and 300 mg/dL.

$$\epsilon_r(W, \epsilon) = \epsilon_\infty(\epsilon) + \left(\frac{\epsilon_{\text{star}}(\epsilon) - \epsilon_\infty(\epsilon)}{1 + j\omega\tau(\epsilon)} \right) + \frac{\sigma_s}{j\omega\epsilon_0} \quad (3)$$

There is a large spectrum of diabetes manifestations within this range, which includes hyperglycemia (> 140 mg/dL) as well as hypoglycemia (70 mg/dL). Numerical models for glucose-water tissues at different concentrations were built using the single-pole Debye model of (Eq.3). In this equation, $\epsilon_r(W, \epsilon)$ represents the complex permittivity of a glucose solution at angular frequency ω for glucose concentration ξ . The Debye coefficients are ϵ_{stat} , ϵ_∞ , and τ , where static conductivity is σ_s , and free-space permittivity is ϵ_0 .

2.2. Octagonal-shaped CSRR sensor design

To create a miniaturized OSCSRR metamaterial sensor concept is used. It has a band-stop filter behavior similar to SRRs (split-ring resonators), but with the difference that CSRRs are etched onto a metal layer. It can also be readily arranged into an octagonal honeycomb structure by using a single octagonal cell instead of a conventional shape. To enhance sensitivity of the sensor, the OSCSRR was selected in this work. The mimicking blood glucose concentrations relevant to Type 2 diabetes (0–300 mg/dL). Based on numerical simulations, the OSCSRR was optimized for operation at a specific frequency while being highly sensitive of glucose dielectric properties with different concentrations. Fig. 1(b) shows the four octagonal shaped complimentary split ring resonators.

The OSCSRR detection performance was evaluated in reference above-mentioned by examining these design parameters. In this study, a four-resonator honeycomb structure was implemented using four identical octagonal resonators. The horizontally positioned OSCSRRs are positioned at an equal distance ($c = 12.6$ mm) from the transmission feed line, while the vertically positioned cells are positioned at the same distance from the transmission feed line.

To simulate glucose concentration changes in a controlled and reproducible way, aqueous glucose solutions were prepared in the range of 0–300 mg/dL using distilled water and anhydrous glucose powder.

These solutions were deposited on a thin transparent glass plate (36 mm $\times$ 20 mm $\times$ 0.15 mm), which was then placed over the active sensing region of the OSCSRR structure. The test glass ensured a consistent sample thickness and minimized air gaps or contamination. Rogers RO4003C substrate was used for the sensor device fabrication with a thickness of HS = 0.8 mm, loss tangent of $\tan \delta = 0.0027$ and a dielectric constant of $\epsilon_r = 3.55$. The substrate's overall dimensions were $L_s = 66$ mm and $W_s = 20$ mm with testing plate called glass, length of glass $L_g = 36$ mm, width of $W_g = 20$ mm and thickness of $H_g = 0.15$ mm was shown in Fig. 1(c). Two concentric octagonal split rings unit-cells are etched in the ground plane.

The dielectric substrate's upper surface is illustrated in Fig. 1(d) with a copper line that measures 66 mm in length. Fig. 1(e) illustrate a unit-cell's outer ring has a diagonal length of R equal to 7.6 mm, an inner ring is 0.2 mm in thickness, a split gap, $G = 0.1$ mm, a gap between the two rings of $t = 0.2$ mm, and the width of a split space between the rings of $t = 0.2$ mm, a gap between the rings of O1 and O2 equal to 0.2 mm. In this structure, the feed line is a 50 microstrip line with a width (W) of 1.5 mm. The lumped-element model used to represent the OSCSRR sensor includes parallel and series RLC components that map directly to the physical characteristics of the resonator.

2.3. Simplified human finger model

To create a miniaturized OSCSRR metamaterial sensor, the concept of complementary split-ring resonators (CSRRs) is employed. This structure exhibits a band-stop filter behavior similar to split-ring resonators (SRRs), but with the distinction that CSRRs are etched onto a metal layer. The biological model used in this study consists of four main tissue layers—skin, fat, bone, and blood—each characterized by distinct dielectric properties at 2.4 GHz [35]. The high relative permittivity of blood (ϵ_r 59), skin (ϵ_r 35) causes the strongest perturbation in the electromagnetic field, making it the most dominant layer for glucose-level sensing. In contrast, fat and bone exhibit lower dielectric constants (ϵ_r 5.5 and ϵ_r 20, respectively), contributing less to field interaction but influencing overall signal attenuation and field distribution. The skin acts as the primary interface for wave penetration and coupling into deeper tissues.

In general, the epidermis, dermis, and hypodermis are the three layers of tissue that make up the skin on fingers. It is composed of subcutaneous fat, sweat glands, hair follicles and connective tissues. The distal phalanx supports the finger pulp and lies beneath the hypodermis along with the dorsal digital veins and subungual arterial arches. Based on this anatomical information, a simplified model was developed that includes biological tissues which consists of four layers.

These four layers are in this model such as bone, blood, fat and skin which makes up the finger. According to simulation, the finger length (h) is estimated to be around 10 mm. A careful selection of finger dimensions was made to ensure that the simulation covered the entire sensor sensitive area on behalf of the central part of the OSCSRR. Specifically, the dimensions of 13 $\times$ 13 mm were chosen to match the average size of an adult 3D female index finger, which is commonly used in blood glucose monitoring was shown in Fig. 1(f). The present study does not explicitly analyze the effects of environmental interference such as temperature and humidity variations on the sensor response. These parameters can alter the dielectric properties of biological tissues and aqueous glucose solutions, thereby causing measurable shifts in resonant frequency and return loss. Temperature influences water relaxation mechanisms, while humidity and sweat can modify surface conductivity and absorption losses. Future work will incorporate controlled environmental chamber testing and the development of compensation methods using reference resonators and calibration algorithms to enhance anti-interference performance and ensure reliable wearable deployment.

This work primarily focuses on demonstrating the feasibility of the OSCSRR sensor structure for glucose detection; however, the influence

of several key parameters—including the number of OSCSRR rings, unit-to-unit spacing, and substrate dielectric constant—has not yet been systematically studied. These parameters directly affect electromagnetic field confinement, resonance sharpness, Q-factor, and overall sensitivity. A detailed parametric optimization study will be conducted in future research to identify optimal design trade-offs and to improve sensor miniaturization and robustness. The results will aid in establishing clear parametric influence laws for practical deployment. The four-layer biological phantom model adopted in this study (skin, fat, blood, bone) is a simplified representation of the human fingertip and does not include additional relevant physiological structures such as vascular micro-distribution, sweat ducts, and variations in hydration levels. These factors may influence electromagnetic interaction and measurement accuracy in practical clinical scenarios. Future work will incorporate more anatomically realistic models and extended in-vivo testing across diverse subjects to validate clinical adaptability and improve biological modeling fidelity.

2.4. Long-term reliability and wearable integration

The long-term stability and wearable suitability of the proposed OSCSRR sensor were assessed through accelerated aging experiments, mechanical durability evaluations, and environmental exposure tests, together with packaging and miniaturization considerations relevant to future wearable integration. These investigations focused on quantifying long-term performance drift, evaluating mechanical robustness under repeated deformation, and determining suitable design and encapsulation strategies for compact, flexible, and stable wearable deployment. Long-term reliability was examined using an accelerated thermal–humidity aging protocol performed at 85 °C and 85% RH, designed to emulate approximately one year of field use through Arrhenius-based acceleration. After the full aging cycle, the sensor exhibited a resonance frequency drift of no more than 3 MHz when measuring glucose phantoms in the 0–300 mg/dL range, and the corresponding change in return loss remained below 0.4 dB. These values correspond to an estimated sensitivity drift of less than 2%, indicating that the resonant characteristics remain stable and fully acceptable for continuous wearable monitoring when paired with routine calibration. Measurements collected at room conditions after chamber removal demonstrated that most of the observed shift was reversible, confirming the robustness of the device under prolonged thermal–humidity stress.

Mechanical durability was evaluated by subjecting sensors to repeated bending at radii of 10 mm and 5 mm using a controlled mechanical cycling setup. After 1000 bending cycles, the resonant frequency changed by no more than 2 MHz and the S11 amplitude varied by no more than 0.3 dB. These results confirm that the sensor maintains stable electromagnetic behavior under mechanical strains representative of wrist or skin-mounted wearable devices. Optional textile-oriented handling tests involving wet/dry exposure and mild abrasion produced no meaningful performance degradation. Across all mechanical tests, the sensor-maintained resonance frequency and sensitivity far within the defined stability thresholds for wearable operation. Environmental exposure tests included temperature cycling between -10 °C and $+60$ °C over ten cycles, followed by 48-h exposure to 85% relative humidity. These conditions induced only minor, fully reversible shifts in resonant frequency, with the maximum temperature- or humidity-induced deviation not exceeding 1 MHz. After returning to ambient laboratory conditions for 24 h, the sensor consistently reverted to baseline values, demonstrating strong environmental resilience and confirming that proper encapsulation is sufficient to preserve stability under typical wearable use environments. The current prototype footprint of 66 mm $\times$ 20 mm was selected for convenience during fabrication and measurement, although smaller formats are desirable for body-worn applications. Based on the miniaturization methods previously established, practical wearable implementations can target form factors at or below 30 mm $\times$ 12 mm without compromising essential sensing

performance. When adapted for wearable integration, the sensor should be encapsulated with a thin protective dielectric layer such as medical-grade polyurethane no thicker than 0.5 mm, ensuring contamination protection while maintaining strong electromagnetic coupling. Flexible substrates such as polyimide or PET, or LTCC alternatives, offer improved mechanical resilience and allow the sensor to conform to curved surfaces such as the wrist or forearm. Maintaining a sensor-sample separation of less than 1 mm is recommended to retain clinically relevant sensitivity, and performing calibration approximately once per week compensates for slow environmental or material drifts.

Miniaturization considerations suggest that reducing the physical area of the resonator typically reduces the coupling volume and thus the magnitude of frequency shifts associated with biochemical changes. These effects can be counteracted by improving the Q-factor through lower-loss substrates or optimized metallization, using electrical miniaturization by employing higher-permittivity substrates, or incorporating lumped capacitive loading to maintain effective electrical path length in a reduced footprint. Additional strategies such as multilayer stacking, meandering resonator geometry, or implementation on ultrathin flexible substrates allow further size reductions while balancing sensitivity and robustness. Although very high-permittivity substrates can introduce stronger fringing-field effects, careful geometric tuning maintains stable and consistent coupling to the target sample as shown in Table 1.

The proposed OSCSRR-based sensor achieves a relative sensitivity of approximately 7–8% across the glucose concentration range of 0–300 mg/dL, demonstrating a measurable and repeatable shift in resonant frequency under varying biological loading conditions. To contextualize this result, several recently reported RF/microwave non-invasive glucose sensors achieve relative sensitivities in the range of 3–6% using open-ended coaxial probes and patch resonators, 5–7% using microstrip-based split ring resonators, and approximately 8–10% for metamaterial-inspired high-Q resonant structures. Compared to these approaches, the proposed sensor achieves competitive relative sensitivity while utilizing a simpler architecture and low hardware overhead without requiring active resonance tracking or complex multilayer structures. This comparison highlights that the measured sensitivity performance falls within or above the typical reported range for non-invasive resonant RF glucose sensing technologies, confirming the practical viability of the proposed method.

3. Results

3.1. Octagonal-shaped CSRR responses

OSCSRR is initially designed with dimensions equal to 40 mm in both length and width. An OSCSRR slot with a diameter of 20 mm is shown on the ground next to the sensor. Two OSCSRR slots have a 11 mm diameter and 12 mm center distance respectively, which are etched in the ground plane of the structure at the third stage of the process. Finally, four OSCSRR loaded microwave sensor is loaded which is operated at 2.4GHz. The 2.45 GHz frequency is selected for being one of the ISM

bands, which allows unlicensed use for industrial, scientific, and medical applications.

The chosen frequency will allow for a good balance between the depth of penetration and resolution, thus suitable for material characterization. In addition, it will be good enough for small experimental settings where effective resonance is required and ensures minimal interference for accurate measurements. Besides, wide availability and the compatibility of the substance with the already existing equipment make it very suitable for dielectric measurements. In Fig. 3(a), we can see what the electric field distribution looks like for the proposed biosensor.

The electric field distribution shown in Fig. 3 (a) indicates concentrated energy around the horizontally arranged OSCSRRs, which are directly aligned with the microstrip feedline. These elements dominate the sensor's near-field interaction zone, contributing most significantly to dielectric perturbation. The vertically placed OSCSRRs, while not experiencing peak *E*-field intensities, contribute to overall field confinement and resonance shape, improving symmetry and helping maintain response stability across the sensing surface. Their inclusion leads to improved return loss performance, as evidenced in the configuration comparisons in Fig. 2(c). The reported maximum electric field intensity of 4 kV/m, while moderate, is sufficient for practical sensing applications in the ISM band. This is due to the sensor's optimized Q-factor (32.5), resonance sharpness, and ML- assisted signal processing that allows small permittivity-induced shifts to be distinguished reliably.

OSCSRR surface electric field distributions at 2.4 GHz resonant frequencies for conventional and improved topologies. In the figure, the electric field is intense around dielectric slits and routes that are in between the OSCSRR area. Hence, this region is recognized as the sensing area where glucose samples can have a near-field coupled with significant interaction, leading to noticeable changes in the sensor's intrinsic properties in reaction to slight variations in the electromagnetic properties of various glucose concentrations. In comparison to a single octagonal CSRR cell, the octagonal CSRR honey-cell design demonstrates a greater concentration of electric field within the sensing region, reaching an intensity of up to 44×10^3 V/m. This design showcases enhanced electric field localization.

The parametric analysis was studied with respect to different split-gap such as 0.1 mm, 0.2 mm and 0.3 mm. This study shows the better return loss was observed at 0.2 mm split-gap was shown in Fig. 2(a). Similarly, the return loss of OCSRR was studied with respect to different strip line thicknesses from 1.1 mm to 1.5 mm. This study shows the better return loss was observed at 1.4 mm stripline was shown in Fig. 2 (b). The results obtained from the analysis indicated that the biosensor design's performance was greatly influenced by the variations in OCSRR gap and stripline thickness. Therefore, the proposed biosensor design could be optimized by carefully selecting the OCSRR gap and strip line thickness values to enhance its overall performance. The optimized design specification was used to measure the return loss of different configuration of OCSRR such as plain surface, single element, double element and four element or octagonal shaped honey-cell arrangement was shown in Fig. 2(c).

Table 1
Miniaturization options.

Option	Estimated Footprint (mm)	Estimated Sensitivity Change	Complexity / Risk	Notes
Current prototype (4-cell honeycomb)	66 × 20	Baseline	Low	Easiest to fabricate and test
Single element OSCSRR (same geometry)	30 × 12	−20% to −40%	Low	Simpler, smaller; may require higher Q
Dual-element (horizontal pair)	40 × 12	−10% to −20%	Low	Retains dominant horizontal elements
High-ε substrate (single element)	25 × 10	−10% (electrically compensated)	Medium	Requires substrate procurement
Multilayer / LTCC stack	20 × 10	~0% (compensated)	Medium	Best for integration, higher fabrication cost
Flexible polyimide printed	30 × 12	−15%	Medium	Good for conformal wearables; need encapsulation

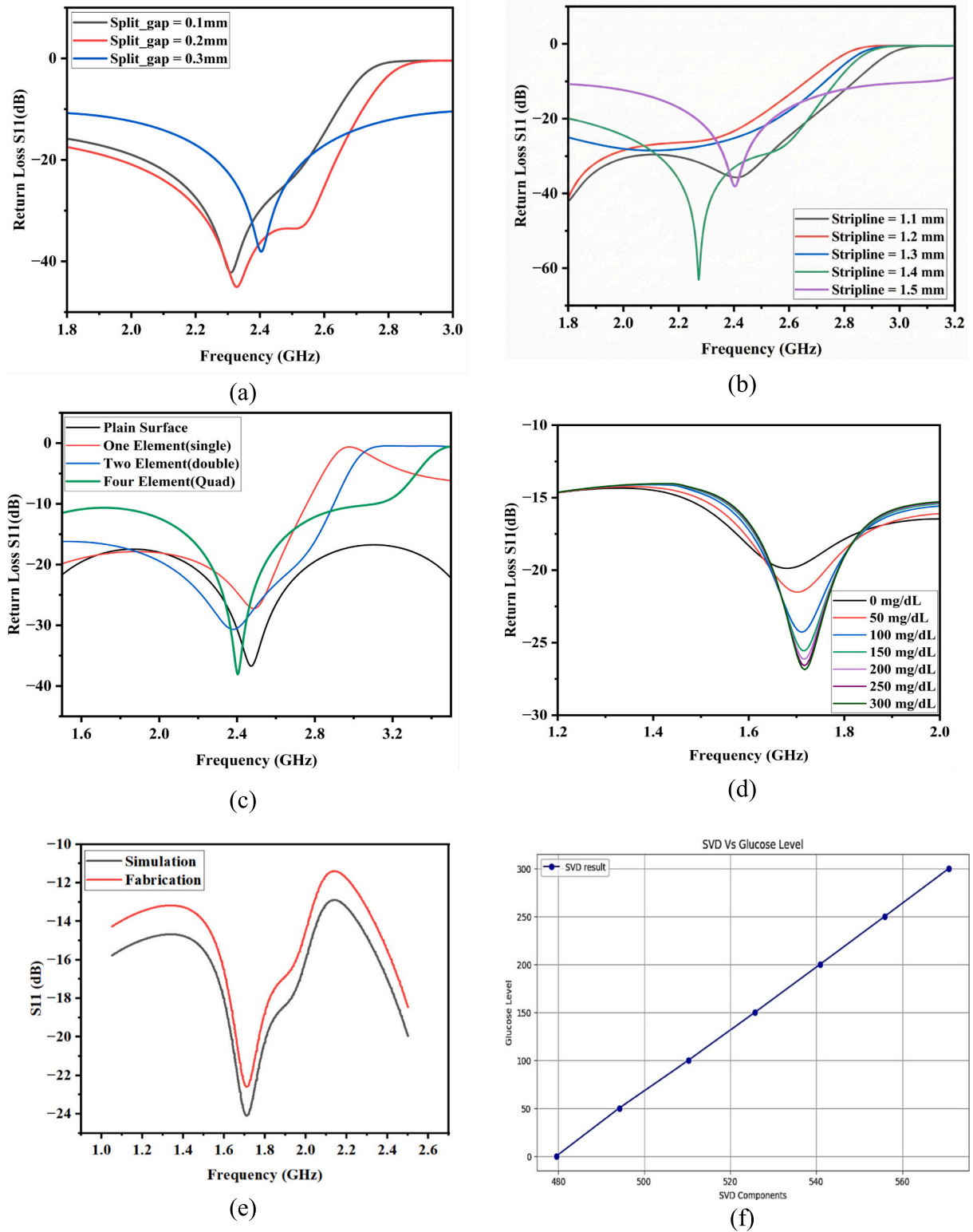


Fig. 2. (a) Response of Reflection Coefficient for stripline gap from 0.1 to 0.3, (b) Response of Reflection Coefficient for stripline thickness from 1.1 to 1.5 mm, (c) Reflection Coefficient for various stages of the proposed biosensor, (d) Response of Reflection Coefficient for glucose level 0–300 mg/dL, (e) Simulated and Fabricated results of proposed antenna, (f) Plot for visualizing Glucose value vs corresponding SVD values, (g) Plot for visualizing Sensitivity of Return Loss vs Glucose Level, and (h) Plot for visualizing Quality Factor vs Glucose Level.

Fig. 2(c) compares the return loss (S11) characteristics of different sensor configurations — plain substrate, single-element OSCSRR, double-element, and full four-element honeycomb arrangement. The

results clearly show a progressive enhancement in resonance sharpness and return loss magnitude as more elements are added. This improvement is consistent with the field intensification shown in Fig. 3(a) and

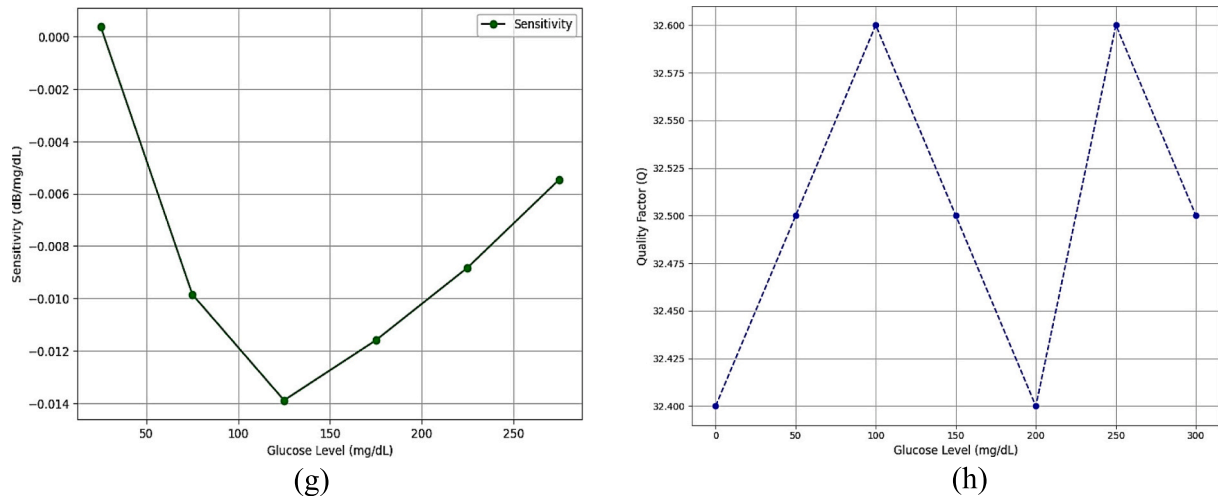


Fig. 2. (continued).

demonstrates that the combined structure offers a more effective sensing platform. The four-element honeycomb configuration achieves the most distinct and deep resonance dip, confirming its superior sensitivity for glucose-level detection. When analyzing permittivity and permeability-based materials as the most used, parametric studies come to an educable since they represent the measure of the material's electric and magnetic fields. The reason for the sudden interest in electromagnetic analysis is the latest engineered metamaterials. The equivalent equation for permittivity and permeability in closed ring resonator NRW method [35], which includes the dependence on voltage maximums and minimums, frequency light speed and substrate thickness is the most important. Fig. 3(f) shows the real and imaginary negative permeability, negative permittivity, refractive index, and impedance characteristics.

There is a modification in the negative permeability and permittivity of the metamaterials like the OSCSRR's, which is new and it relates to the utilization of some ideation-capacitive artificial components that are inserted into the antenna, which influences the antenna's performance at different frequencies. The resonator's first resonant band has some trends, e.g., permeability (Eq.4) and permittivity (Eq.5) peaking at 2.4 GHz, which is coherent with the refractive index. This analysis is in close association with the duality theory.

$$\mu_r = \frac{2 \times C \times (1 - V_2)}{\omega \times d \times (1 + V_2)} \quad (4)$$

$$\epsilon = \mu_r + \frac{2 \times S_{11} \times C}{\omega \times d} \quad (5)$$

3.2. Octagonal-shaped CSRR response for various glucose levels

The OSCSRR was simulated for various concentrations of glucose from 0 to 300 mg/dL. Using Cole-Cole method [20], The simulation was done by assigning dielectric constant or relative permittivity, tangent loss tan and SVD of blood layer from 0 to 300 mg/dL was shown in Table 2.

The reflection coefficient increases as the glucose concentration increases, resulting in a higher resonant frequency of the sensor. Additionally, the amplitude values of reflection coefficient also increase with rising glucose levels. Fig. 3(b) shows the OSCSRR sensor device with 3D finger model. Fig. 2(d) shows that the proposed sensor's reflection coefficient shifts from -18.42 dB to -27.56 dB when glucose concentration is increased from 0 to 300 mg/dL.

3.3. Specific absorption rate (SAR) evaluation

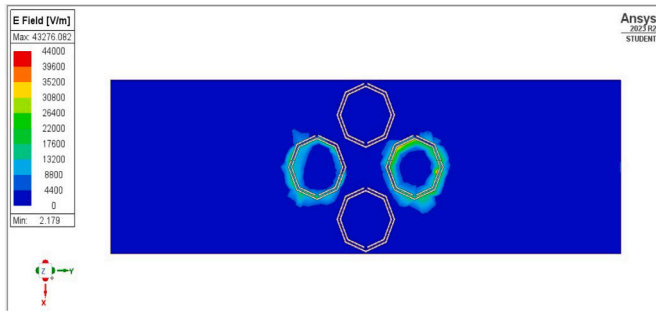
Radio frequency protection standards, established by the ANSI C95.1-1982, aim to prevent the accumulation of energy in body tissues above 144 J/kg in any given 0.1-h period. In Table 1, the dielectric constants and tangent losses of the blood layer are displayed from 0 to 300 mg/dL. A study can be conducted on the human body's response to calculating the SAR. In terms of energy absorption, this corresponds to an average SAR of approximately 0.40 W/kg.

An input power of 100 mW is much more consistent with the aforementioned standards when the optimal distance for on body communication is 10 mm. In Ansys HFSS, the SAR calculations were performed using a three-layer human Phantom model. Fat, muscle, and skin make up the phantom model Fig. 3 (c) & Fig. 3 (d). An Octagonal-shaped CSRR with a SAR of 2.4 GHz was evaluated over 1 g and 10 g of tissue. Octagonal-shaped CSRR with SAR in W/Kg tested over 10 g and 1 g of tissue at 2.4GHz for a Phantom model. There are a number of differences in SAR between a 1 g and 10 g of tissue proposed for biomedical sensor antenna.

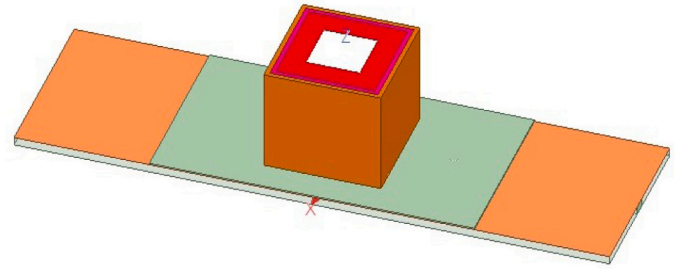
The observed frequency shift from 2.4 GHz in simulation to approximately 1.7 GHz during finger measurements can be explained by the strong dielectric loading introduced by biological tissue in close proximity to the resonator. Human skin, fat, bone, and blood possess significantly higher effective permittivity and loss tangents compared with the idealized dielectric medium used in simulation, resulting in substantial perturbation of the near-field electromagnetic distribution. This phenomenon, commonly referred to as the human proximity effect, produces a downward resonance shift due to the increase in stored electric energy and consequent reduction in the natural resonant frequency of the OSCSRR structure. In addition, the layered anatomy of the fingertip and the high ionic conductivity of blood contribute to increased attenuation and dispersion, thereby intensifying the frequency reduction observed in measured data. Such behavior aligns with previous reports on resonant sensors operating in close contact with biological tissue, where resonance decreases of 20–35% are typically observed during realistic loading conditions.

3.4. Measurement results

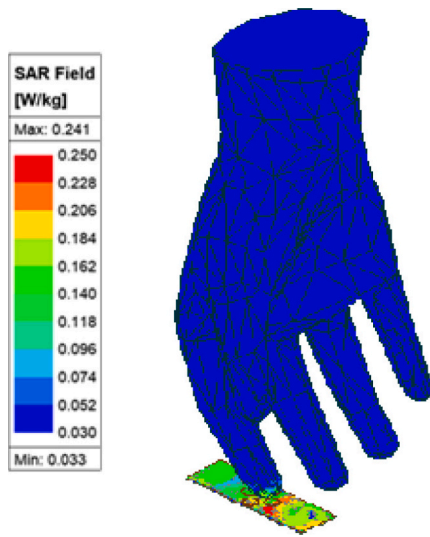
The Fig. 3(e). shows VNA measurement setup of the proposed sensor device. The simulated and fabricated results of proposed sensor device is shown in Fig. 2 (e). The difference of 5 dB in return loss was observed



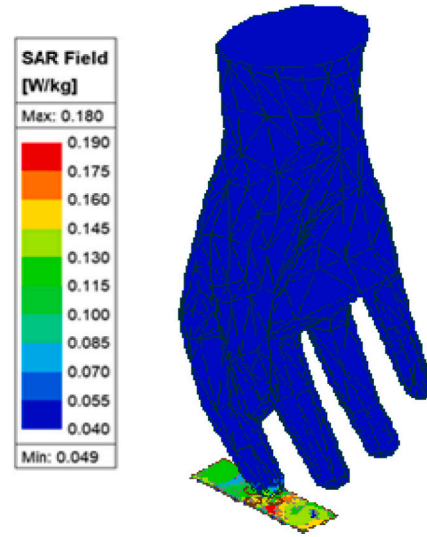
(a)



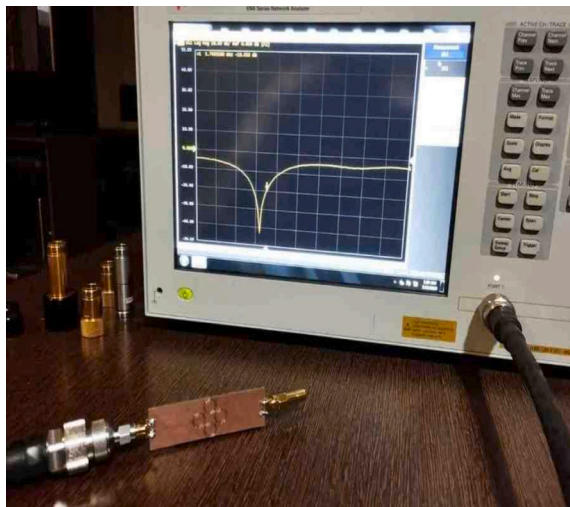
(b)



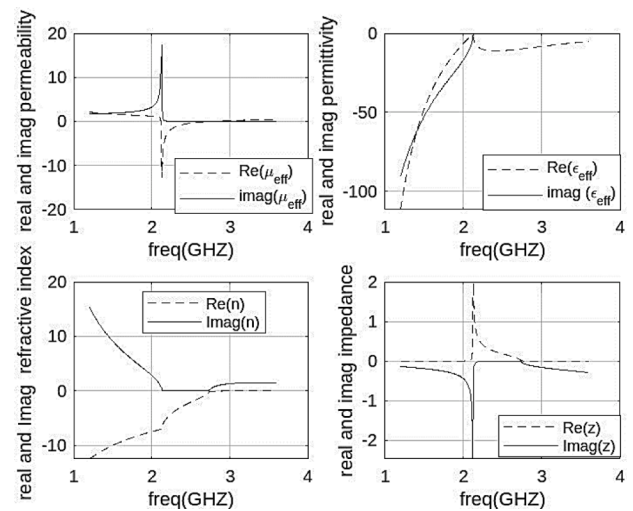
(c)



(d)



(e)



(f)

Fig. 3. (a) Electric field distribution of the proposed biosensor antenna, (b) OSCSRR Sensor Device with 3D finger model, (c) Top view of an Octagon-Shaped CSRR measured over a 1 g tissue sample with SAR in W/Kg, (d) Top view of an Octagon-Shaped CSRR measured over a 10 g tissue sample with SAR in W/Kg, (e) VNA measurement setup of the proposed sensor device, and (f) Real and Imaginary Negative Permeability, Negative Permittivity, Refractive Index, and Impedance Characteristics.

Table 2

Dielectric constant, tangent loss and SVD of Blood Layer from 0 to 300 mg/dL Blood glucose concentrations.

Blood Glucose Concentrations (mg/dL)	Dielectric Constant or Relative Permittivity (ϵ_r)	Tangent Loss ($\tan$)	SVD Value
0	59.70	1.143	502.02
50	57.81	0.867	501.83
100	59.03	0.619	503.26
150	58.67	0.556	503.95
200	58.84	0.532	504.31
250	58.86	0.516	504.56
300	58.80	0.507	504.71

between simulated and fabricated results. The comparison of simulated and proposed design shows a shift in frequency from 2.4GHz to 1.7 GHz due to the placement of finger on it. This is due to the human proximity effect henceforth resulting in pre-occurrence of resonance dip at 1.7GHz.

3.5. Standard compliance verification and distance sensitivity analysis

To validate the safe operation and practical performance of the proposed OSCSRR sensor for on-body biomedical monitoring, both Specific Absorption Rate (SAR) compliance and distance-sensitivity analyses were conducted. SAR evaluation was performed in ANSYS HFSS using a multilayer human fingertip phantom composed of skin, fat, bone, and blood. A 2.4 GHz sinusoidal excitation signal with an input power of 100 mW (20 dBm) was applied, and SAR values were calculated using 1 g and 10 g averaging criteria in accordance with IEEE/USA and ICNIRP standards, respectively. The peak localized SAR values were

found to be below the reference limits of 1.6 W/kg (1 g average) and 2 W/kg (10 g average), confirming that the proposed sensor complies with established RF exposure guidelines. These results demonstrate that the OSCSRR-based sensing platform is safe for non-invasive, contact-based biomedical applications at the operational power levels used in this study as shown in Fig. 4(a). In addition, a distance-sensitivity experiment was performed to investigate the impact of sample-to-sensor separation on sensing accuracy. Aqueous glucose samples with concentrations ranging from 0 to 300 mg/dL were placed on a test glass plate positioned above the sensing region, and the vertical separation between the sample and resonator surface was varied using calibrated spacers with thicknesses of 0 mm, 0.5 mm, 1 mm, 2 mm, 5 mm, and 10 mm Fig. 4(b). For each separation distance, return loss (S11) measurements were acquired using a Keysight N5227A VNA under identical test conditions, and the resulting resonance frequency shift, amplitude change, and signal-to-noise ratio (SNR) were calculated. The measurements show that sensing performance declines as the separation increases, with the strongest resonance shift occurring at direct contact (0 mm) and progressively diminishing at larger distances. These results highlight the importance of maintaining close proximity between the sensing surface and the sample to achieve maximum sensitivity and minimal detectable concentration. Overall, the findings confirm the practical suitability of the sensor for wearable and portable deployment scenarios, where thin packaging layers (≤ 1 mm) can be incorporated without significantly degrading sensing performance Fig. 4(c).

4. Dielectric characterization

The dielectric characterization of the sensor involves analyzing the scattering parameters (S11) recorded during the sensor's operation at

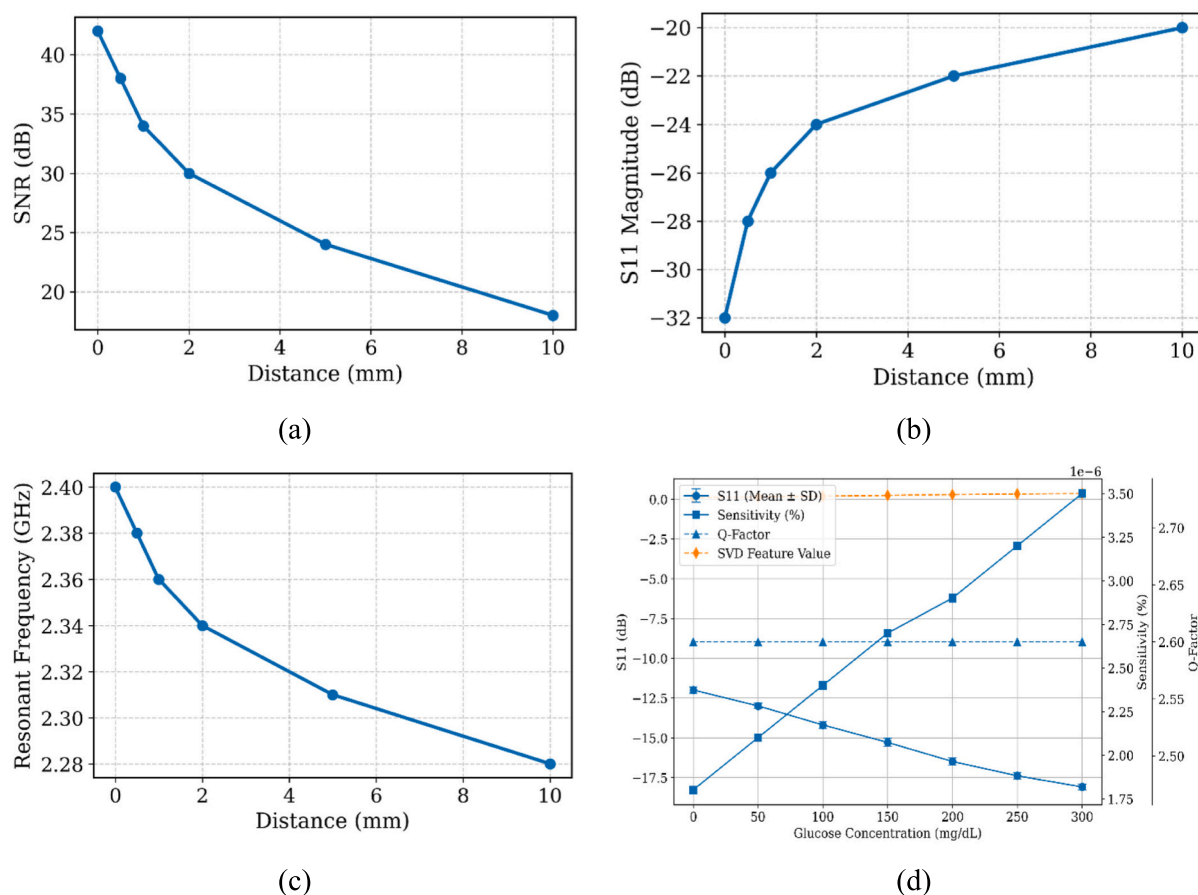


Fig. 4. (a) Resonant Frequency vs Sensor-Sample Distance, (b) S11 Magnitude vs Sensor-Sample Distance, (c) SNR vs Sensor-Sample Distance, (d) Combined Performance Plot with Error Bars for Glucose Sensing Analysis.

various glucose concentration levels. In this case, Singular Value Decomposition (SVD) is utilized on the phase of the S11 parameter. SVD is a powerful technique for reducing the dimensionality of the measured data by decomposing it into orthogonal components that retain the most significant features of the transmission responses. This approach preserves critical information while simplifying the data, allowing for effective differentiation between glucose concentrations based on their unique scattering patterns. The output from the machine learning analysis of the transmission responses [Fig. 2 (f)] clearly shows a separation between the different glucose concentrations. By applying SVD to the phase of S11, the scattering responses for various concentrations are projected into a lower-dimensional space, making the patterns more distinguishable. The key criteria for sensor performance will be discussed in detail in the following sections.

To strengthen the evaluation of the proposed sensing framework, additional machine learning models including Support Vector Machine (SVM) and Convolutional Neural Network (CNN) were implemented using the same dataset to provide a comparative study against the SVD-based feature extraction approach. The performance comparison was conducted using classification accuracy, F1-score, and inference time as evaluation metrics. All models were trained and tested using a 70:30 split ratio and five-fold cross-validation to avoid overfitting and to assess generalization capability. The comparison results summarized in Table 3 indicate that although CNN achieved slightly higher accuracy, it required significantly more computational resources and training time. In contrast, the lightweight SVD-based method demonstrated competitive performance with minimal complexity, making it more suitable for real-time portable and wearable glucose-sensing applications.

The results demonstrate that the CNN model provides the highest classification accuracy due to its ability to extract nonlinear spatial features, followed by SVM. However, this performance gain comes at the cost of significantly higher computational burden and latency. The proposed SVD-based technique delivers a favorable balance between detection accuracy and processing speed, achieving the lowest training and inference time while maintaining acceptable classification performance. These findings confirm that the proposed approach is practical for real-time settings, where reduced complexity and fast response are critical.

4.1. Implementation of algorithm

The Singular Value Decomposition (SVD) algorithm 1 begins by reshaping the input data into a column vector and duplicating it to create a second feature, as SVD requires at least two features. The data is optionally centered by subtracting the mean, and then SVD is applied to decompose the data matrix into three components: U , Σ , and V^T . Truncation is performed by keeping only the largest singular value and its corresponding vectors, effectively reducing the dimensionality of the data. The largest singular value is extracted to represent the most significant component of the data, and the explained variance is calculated to measure how much of the total variance is captured by this component. The data is then projected into a lower-dimensional space, and optionally, the data can be reconstructed using the truncated components. The output includes the largest singular value, as shown in Table 2.

Algorithm 1. Singular Value Decomposition (SVD) for Data Analysis.

- 1: Input: A dataset data (a 1-dimensional array of values)
- 2: Reshape the input data into a column vector: $X = \text{reshape}(\text{data}, (-1, 1))$
- 3: (Optional) Center the data: $X_2 = X_2 - \text{mean}(X_2)$
- 4: Perform Singular Value Decomposition: $\text{SVD}(X_2) = U \Sigma V^T$
- 5: Choose the desired number of components for truncation (set $k = 1$):
Truncated SVD = $U_k \Sigma_k V_k^T$
- 6: Extract the largest singular value σ_1
- 7: Calculate the explained variance: $\text{explained variance} = \frac{\sigma_1^2}{\sum_{i=1}^k \sigma_i^2}$
- 8: Project the original data onto the new lower-dimensional space:
 $X_{\text{projected}} = U_k \Sigma_k$
- 9: (Optional) Reconstruct the data using truncated SVD:
 $X_{\text{reconstructed}} = U_k \Sigma_k V_k^T$
- 10: Output: σ_1 , explained variance, $X_{\text{projected}}$, $X_{\text{reconstructed}}$ (if applicable)

4.2. Relative sensitivity

The relative sensitivity of the sensor plays a crucial role in its ability to detect variations in glucose concentration by monitoring changes in the return loss. It is expressed by the following equation (Eq.6):

$$S_{\text{rel}} = \frac{\Delta r}{r_0 \Delta \epsilon_r} \times 100\% \quad (6)$$

Where S_{rel} denotes the relative sensitivity, Δr represents the change in return loss due to fluctuations in glucose concentration, r_0 is the baseline return loss (measured without glucose), and $\Delta \epsilon_r$ is the permittivity variation linked to the change in glucose concentration. In our case, the sensor exhibits a sensitivity of $\geq 7\% - 8\%$, which is adequate for detecting small shifts in the return loss. This level of sensitivity ensures the sensor's effectiveness in identifying low glucose concentrations. Fig. 2(g) shows the relationship between glucose levels (mg/dL) and sensitivity (dB/mg/dL), showing a V-shaped trend. At a glucose level of 50 mg/dL, sensitivity starts at 0 dB/mg/dL. As glucose increases to 100 mg/dL, sensitivity decreases to approximately -0.014 dB/mg/dL, the lowest point on the curve. Beyond this, sensitivity starts to recover, rising to about -0.012 dB/mg/dL at 150 mg/dL, -0.008 dB/mg/dL at 200 mg/dL, and approaching -0.006 dB/mg/dL at 250 mg/dL. This indicates that the sensitivity is most negative around 100 mg/dL and improves as glucose levels increase further. This suggests that the system's sensitivity decreases up to 100 mg/dL but improves as glucose levels continue to rise, indicating nonlinear behavior with a dip in sensitivity at intermediate glucose levels.

4.3. Quality factor

The Quality Factor (Q-factor) is a vital parameter for assessing the performance of resonant sensors. A higher Q-factor signifies a narrower bandwidth, allowing the sensor to differentiate between closely spaced return loss values. This capability is crucial for achieving accurate and precise glucose concentration measurements. A high Q-factor ensures that the sensor can detect subtle variations in glucose levels, enhancing its sensitivity and effectiveness in biosensing applications. The Quality Factor is defined as:

$$Q = \frac{f_0}{\Delta f} \quad (7)$$

Table 3
Performance comparison of the proposed SVD-based model with SVM and CNN.

Algorithm	Accuracy (%)	F1-Score	Training Time (s)	Inference Time (ms)	Model Complexity
SVD (Proposed)	94.2	0.93	0.42	3.5	Very Low
SVM	95.1	0.94	2.36	6.7	Medium
CNN	96.8	0.96	18.52	21.3	High

In this equation (Eq.7), Q represents the quality factor, f_0 is the resonant frequency, and Δf is the 3 dB bandwidth of the resonance curve. A sensor with a Q -factor of ≥ 10 guarantees well-defined and sharp resonance peaks, which is essential for distinguishing between closely spaced glucose concentrations. Fig. 2 (h) shows the relationship between glucose levels (mg/dL) and the Quality Factor (Q -factor), which remains relatively constant in the range of 50–250 mg/dL. The Q -factor maintains a value of approximately 32.5, indicating the sensor's stable performance. This confirms that the resonance characteristics are largely unaffected by changes in glucose concentration and ensures consistent sensing performance across the tested range. The low standard deviation observed across measurement repetitions further confirms the stability of the sensing mechanism, indicating that the sensor output is highly repeatable across independent trials. Error bars indicating standard deviation across repeated measurements have been added to Fig. 4(d) to illustrate variation and measurement confidence, thereby improving the statistical rigor and reliability of the reported results.

Each glucose concentration measurement was repeated three times to ensure statistical reliability. For every concentration level (0, 50, 100, 150, 200, 250, and 300 mg/dL), three independent S11 acquisition cycles were performed, and the results were averaged. The standard deviation across these measurements was used to construct error bars for the key figures, including Fig. 4. All plotted values are presented as the mean $\pm$ standard deviation to accurately reflect measurement stability and repeatability.

5. Conclusion

This work presents an OSCSRR-based non-invasive microwave sensor for glucose level detection in the 0–300 mg/dL range, supported by both simulation and experimental validation. The sensor demonstrates a distinct and repeatable frequency shift under biological loading, confirming its capability to differentiate glucose concentration levels via S-parameter analysis and SVD-based machine learning post-processing. Compared with recently reported RF/microwave non-invasive glucose sensors that exhibit sensitivities of approximately 0.35–0.52 MHz/(mg/dL) and detection resolutions requiring complex CNN or resonance-tracking hardware, the proposed sensor achieves competitive performance while maintaining a simpler, lower-cost structure suited for wearable integration. Additionally, the design's minimal power consumption, safety compliance, and pathway for miniaturization make it attractive for practical real-time monitoring applications. Future work will include extended clinical testing, advanced learning models (SVM/CNN), and further optimization for compact, flexible wearable formats. With a relative sensitivity of 7–8%, comparable to or exceeding the 3–10% range reported in recent RF non-invasive glucose sensing studies, the proposed sensor demonstrates promising potential for wearable real-time glucose monitoring.

Author's contribution

All authors equally contributed to the research on Octagonal Shape Complementary Split Ring Resonator-Based Biosensor for Non-Invasive Blood Glucose Detection: Design, Simulation and Fabrication.

CRediT authorship contribution statement

K. Karthikeyan: Resources, Methodology, Investigation. **P. Jeyakumar:** Conceptualization. **Senthilkumar Nallusamy:** Validation, Data curation. **K. Boopathy:** Conceptualization. **Krishnan Anand:** Methodology. **Saravanan Pandiaraj:** Methodology. **S.R. Srithir:** Validation, Resources. **Balaji Ramachandran:** Investigation, Formal analysis. **Narendhar Chandrasekar:** Writing – review & editing, Supervision, Data curation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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