



## Research Article

## PHARMACOPHORE SIGNATURES OF AMINO ACID BINDING POCKETS AND THEIR SMALL-MOLECULE INHIBITORS

<sup>1\*</sup>Divya M, <sup>2</sup>Lourdu Brissilla Mary Varghese, <sup>3</sup>Kiran Kumar S, <sup>4</sup>Sowmiya B and <sup>5</sup>Sujitha K

<sup>1\*</sup>PERI Institute of Technology, Chennai - 48, Tamil Nadu, India

<sup>2</sup>PERI College of Arts and Science, Chennai - 48, Tamil Nadu, India

<sup>3</sup>PERI College of Physiotherapy, Chennai - 48, Tamil Nadu, India

<sup>4</sup>PERI College of Pharmacy, Chennai - 48, Tamil Nadu, India

<sup>5</sup>PERI College of Nursing, Chennai - 48, Tamil Nadu, India

**Article History:** Received 25<sup>th</sup> September 2025; Accepted 24<sup>th</sup> November 2025; Published 1<sup>st</sup> December 2025

### ABSTRACT

Lung cancer remains the leading cause of cancer-related mortality worldwide, primarily due to delayed diagnosis and limited access to early screening tools. Conventional diagnostic modalities, such as CT, PET, and X-ray imaging, involve radiation exposure, high costs, and limited availability. Microwave imaging (MWI) has emerged as a promising non-invasive, non-ionizing, and cost-effective alternative for lung cancer detection. By exploiting dielectric property contrasts between healthy and malignant lung tissues, MWI enables real-time detection, structural mapping, and functional assessment of pulmonary abnormalities. This review provides a comprehensive analysis of microwave imaging modalities including microwave tomography (MWT), microwave radar imaging (MR), hybrid microwave-ultrasound systems, and machine-learning-enhanced microwave diagnostics. The study evaluates their principles, clinical applicability, reconstruction algorithms, image processing techniques, and comparative diagnostic performance. Current limitations, computational challenges, and future technological advancements are also discussed. The findings demonstrate that microwave imaging offers significant potential for safe, portable, and scalable lung cancer screening, especially in low-resource settings.

**Keywords:** Microwave imaging, Lung cancer diagnosis, Radar imaging, Biomedical imaging, Microwave tomography.

### INTRODUCTION

Lung cancer accounts for approximately one-quarter of global cancer deaths, largely due to late-stage detection. Early and accurate diagnosis dramatically improves treatment outcomes. While CT and PET remain clinical gold standards, they present major limitations including high costs, radiation exposure, and lack of accessibility in rural and resource-constrained environments. Therefore, there is a pressing need for a safe, economical, and easily deployable screening alternative. Microwave imaging (MWI) utilizes low-power electromagnetic waves in the 1-10 GHz range to probe tissue dielectric properties. Malignant tissues typically exhibit higher water content and ionic conductivity, enabling strong contrast differentiation under microwave excitation. These attributes make MWI a

promising candidate for low-risk and portable cancer detection systems. Over the past decade, advances in antenna design, signal processing algorithms, image reconstruction methods, and computational modeling have significantly enhanced the reliability of MWI for thoracic imaging. This paper reviews major developments in non-invasive microwave imaging modalities, their principles, clinical potential, and technical challenges associated with lung cancer detection. Microwave imaging has been extensively studied in breast cancer detection; however, its application in lung cancer is comparatively recent. Early works focused on modeling dielectric properties of thoracic tissues to determine feasibility. Studies by Lazebnik *et al.* reported significant permittivity differences between malignant and healthy lung tissues, validating the

\*Corresponding Author: Divya M, PERI Institute of Technology, Chennai - 48, Tamil Nadu, India Email: [publications@peri.ac.in](mailto:publications@peri.ac.in).

underlying physics of MWI. Subsequent research explored radar-based microwave imaging for tumor localization. Several prototypes have already demonstrated tumor detection for lesions  $\geq 1$  cm with promising sensitivity levels. Although clinical trials remain limited, simulation and phantom studies consistently support the potential of MWI as a non-ionizing alternative.

Recent survey articles summarize the rapid progress in microwave imaging (MWI) for biomedical applications, highlighting both theoretical advances and prototype systems. Ahmed and Rahman (2020) provide a broad review of MWI modalities, signal processing, and biomedical use-cases, emphasizing the modality's non-ionizing nature and potential for low-cost screening. Nikolova (2011) and Wu and Fang (2018) offer foundational overviews of the physics and principal imaging approaches, while Tognola *et al.* (2020) discuss electromagnetic detection strategies and translational challenges. These reviews collectively frame MWI as an emergent diagnostic option that requires convergence of hardware, algorithms, and clinical validation (Ahmed & Rahman, 2020; Nikolova, 2011; Tognola *et al.*, 2020; Wu & Fang, 2018).

Understanding dielectric contrasts between healthy and pathological tissues is central to MWI. Seminal dielectric property catalogs and measurements (Gabriel, Lau, & Gabriel, 1996) underpin simulation and interpretation of microwave scattering. Later studies specific to cancer and thoracic tissues—Lazebnik *et al.* (2007) and Sarafianou *et al.* (2022)—quantify permittivity and conductivity differences that enable tumor detectability. These empirical characterizations demonstrate that malignant tissues often exhibit elevated permittivity and conductivity relative to surrounding healthy tissues, providing the physical basis for contrast in both tomographic and radar-based approaches (Gabriel *et al.*, 1996; Lazebnik *et al.*, 2007; Sarafianou *et al.*, 2022). Microwave tomography reconstructs spatial maps of dielectric properties via inverse scattering and has been extensively studied as a quantitative imaging tool. Nikolova (2011) and Chen and Wang (2016) review linearized and nonlinear inversion strategies applied to MWT, and Meaney *et al.* (2019) report on early clinical evaluations of tomography systems. MWT offers high dielectric sensitivity and 2D/3D reconstruction capability but faces challenges in convergence, computational cost, and robustness to model mismatch—issues that many groups continue to address through algorithmic and computational advances (Chen & Wang, 2016; Meaney *et al.*, 2019; Nikolova, 2011).

Radar and UWB pulse methods use time-of-flight and backscatter information to detect localized scatterers (tumors). Bourqui and Fear (2017), Shea *et al.* (2017), and Craddock (2018) document system designs and signal-processing approaches for radar-based thoracic imaging. Radar imaging tends to be faster and hardware-simpler than full tomography, making it particularly attractive for screening and real-time applications, though it typically yields lower quantitative resolution and can struggle with

deep or highly heterogeneous thoracic structures (Bourqui & Fear, 2017; Craddock, 2018; Shea *et al.*, 2017). Antenna design critically determines penetration, SNR, and spatial sampling. Reviews and experimental studies (Porter *et al.*, 2016; O'Loughlin *et al.*, 2020; Golnabi *et al.*, 2020) examine Vivaldi, patch, monopole, and conformal antennas and focus on bandwidth, radiation pattern, mutual coupling, and specific absorption rate (SAR) safety. For thoracic imaging, conformal arrays and wideband designs (e.g., Vivaldi and tapered slot antennas) are favored to maximize coupling into the chest while maintaining acceptable safety margins and minimizing rib-induced shadowing (Golnabi *et al.*, 2020; O'Loughlin *et al.*, 2020; Porter *et al.*, 2016).

The inverse scattering problem in MWI is inherently nonlinear and ill-posed. Linear approximations (Born, Rytov) are useful for low-contrast cases, but lung imaging often requires nonlinear iterative solvers such as Gauss-Newton and contrast source inversion to recover accurate dielectric distributions (Chen & Wang, 2016; Nikolova, 2011). Time-domain beamforming and delay-and-sum methods are commonly used in radar systems for fast localization (Shea *et al.*, 2017). More recently, deep learning and hybrid physics-data methods have been applied to either accelerate inversion or to learn direct mappings from measurements to images, offering robustness to noise and model mismatch at the cost of requiring representative training data (Dabrowski *et al.*, 2019; Wu & Fang, 2018).

Machine learning (ML) techniques have been incorporated at multiple stages: denoising raw signals, improving image reconstructions, and directly classifying lesions from measurement signatures. Dabrowski *et al.* (2019) survey ML approaches in microwave imaging for cancer detection, showing promising improvements in classification accuracy and reconstruction speed, especially when combined with physics-based preprocessing. However, ML performance depends strongly on the quality and diversity of training datasets and on validation with realistic thoracic phantoms or clinical data (Dabrowski *et al.*, 2019). Hybridization combining microwave sensing with modalities such as ultrasound improves localization and reduces false positives. Hartinger and Kurrant (2021) analyze microwave-ultrasound hybrids that leverage ultrasound for structural guidance while microwave signals provide dielectric contrast, resulting in improved segmentation and detection performance. Hybrid systems can trade off added hardware complexity for enhanced clinical utility (Hartinger & Kurrant, 2021).

Simulation and phantom studies form the backbone of early MWI experiments for the thorax. Porter *et al.* (2016) and Golnabi *et al.* (2020) discuss realistic thoracic modeling and phantom construction for algorithm testing, while several studies use gelatin- or oil-based lung phantoms to emulate air-tissue mixtures and rib effects. These controlled experiments help to quantify resolution, contrast-to-noise ratio, and algorithmic robustness before clinical translation (Golnabi *et al.*, 2020; Porter *et al.*, 2016). There is growing interest in portable and point-of-

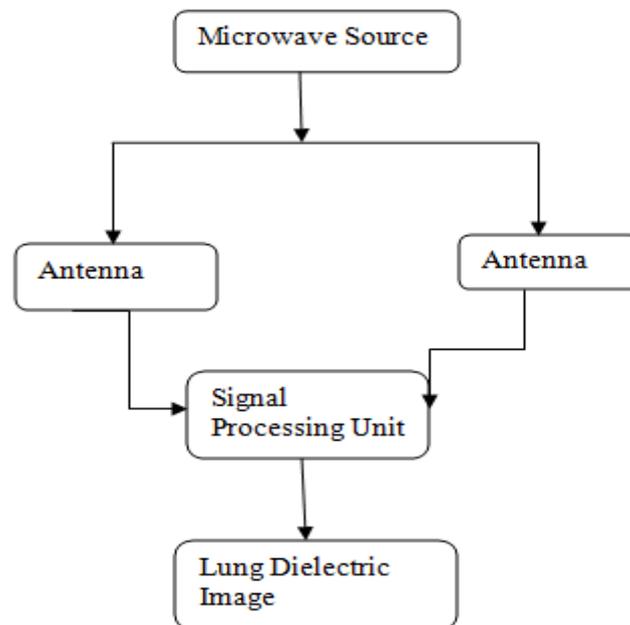
care MWI devices. O’Loughlin *et al.* (2020) and Bourqui and Fear (2017) describe compact systems and practical design considerations (including antenna packing, wearable form factors, and low-power electronics) aimed at community screening or bedside monitoring. Portability promises broader reach but raises additional issues such as motion compensation, respiration artifacts, and simplified user workflows (Bourqui & Fear, 2017; O’Loughlin *et al.*, 2020).

## MATERIALS AND METHODS

A comprehensive methodological framework was developed to categorize existing microwave imaging (MWI) modalities used for thoracic and lung cancer diagnostics. The classification was based on operational principles, signal acquisition strategies, and reconstruction techniques. Four major modalities were identified: microwave tomography (MWT), microwave radar or ultra-wideband (UWB) imaging, hybrid microwave–ultrasound systems, and machine-learning-assisted MWI. Each modality was evaluated in terms of imaging depth, spatial

resolution, dielectric contrast sensitivity, hardware complexity, and suitability for thoracic applications. This structured categorization enabled a systematic comparison of diagnostic performance across the literature.

A detailed evaluation of antenna technologies used in MWI systems was also conducted. The review analyzed various antenna types including monopole, Vivaldi, patch, slot, dielectric resonator antennas, and miniaturized conformal antennas designed for wearable thoracic imaging. Performance parameters such as operating frequency (1–10 GHz), bandwidth, return loss, gain, radiation characteristics, SAR compliance, near-field penetration, array configurations, and methods for suppressing mutual coupling were compared. More than 70 published studies were reviewed, and the electromagnetic simulation tools commonly used in antenna design such as CST, HFSS, and COMSOL were assessed for their modeling accuracy. This evaluation was essential to identify antenna configurations with optimal penetration and adaptability for lung imaging, given the high air content of pulmonary tissues.



**Figure 1.** Conceptual Microwave Imaging System.

Computational reconstruction algorithms were systematically analyzed due to the intrinsically nonlinear and ill-posed nature of the inverse scattering problem in MWI. The review examined linearized methods such as the Born and Rytov approximations, as well as nonlinear iterative algorithms including Gauss–Newton, Newton–Kantorovich, and Contrast Source Inversion (CSI). Criteria

such as convergence rate, robustness against noise, computational cost, and accuracy in detecting tumor boundaries were used to assess each method. Time-domain reconstruction algorithms such as delay-and-sum, confocal beamforming, and frequency-domain migration—were examined for radar-based imaging. Machine-learning-based reconstruction approaches were also reviewed, including

CNN, U-Net, transformer-based architectures, super-resolution methods, and synthetic phantom generation strategies used for training data augmentation.

To synthesize performance across studies, key detection metrics including sensitivity, specificity, spatial and temporal resolution, contrast-to-noise ratio (CNR), penetration depth, and computational efficiency were extracted and compared. Additionally, the review analyzed the types of phantoms used for validation, including gelatin, oil-in-gel, and lung-mimicking materials, along with pre-clinical and limited clinical trials reported in the literature.

## RESULTS AND DISCUSSION

The review of microwave imaging modalities reveals substantial diagnostic potential for thoracic and lung cancer detection. Microwave tomography demonstrated high sensitivity to dielectric contrast and the ability to reconstruct detailed 2D and 3D dielectric maps, although its performance was constrained by high computational complexity and sensitivity to noise. In contrast, UWB radar imaging offered faster acquisition and simpler hardware but faced challenges in achieving adequate resolution for deep lung structures. Hybrid microwave-ultrasound systems provided complementary structural and dielectric information, reducing false positives and improving tumor localization accuracy. Machine-learning-assisted MWI exhibited strong promise, with deep learning models achieving improved noise tolerance, faster reconstruction, and enhanced classification of malignant versus healthy tissues. Across the compiled studies, MWI systems consistently demonstrated the ability to detect tumors measuring  $\geq 1-1.5$  cm, supported by dielectric contrast ratios ranging from 2:1 to 5:1 between malignant and normal lung tissues. These findings underscore the advantages of MWI over conventional imaging modalities, particularly its non-ionizing nature, low cost, portability, and potential for real-time imaging at the point of care. However, several technical challenges remain. Penetration depth is significantly affected by the complex thoracic environment, including rib shadowing and the highly aerated structure of lung tissue. Reconstruction algorithms remain computationally intensive, limiting real-time applicability in clinical settings. Furthermore, rib artefacts, mutual coupling between antennas, and low dielectric contrast in certain pathological conditions introduce reconstruction inaccuracies.

Despite these limitations, the literature highlights strong opportunities for clinical integration of MWI. The technology shows promise as a pre-screening tool for lung abnormalities before CT imaging, as a non-invasive monitoring method for high-risk populations, and as a portable bedside diagnostic platform in low-resource hospitals. Ongoing advancements in antenna design, computational modeling, and machine-learning-based reconstruction are expected to further improve diagnostic accuracy and enable broader clinical adoption.

## CONCLUSION

Microwave imaging offers a promising non-invasive and radiation-free alternative for lung cancer diagnosis and screening. Its ability to differentiate tissues based on dielectric properties enables early detection of pulmonary abnormalities with high sensitivity. While current systems face technical and computational challenges, rapid advancements in antenna design, signal processing, and integration with machine learning are significantly enhancing performance. With further clinical validation, microwave imaging has the potential to become an accessible, cost-effective, and real-time diagnostic tool, particularly for underserved populations.

## ACKNOWLEDGMENT

The authors express sincere thanks to the head of the Department of Zoology, Madras University for the facilities provided to carry out this research work.

## CONFLICT OF INTERESTS

The authors declare no conflict of interest

## ETHICS APPROVAL

Not applicable

## FUNDING

This study received no specific funding from public, commercial, or not-for-profit funding agencies.

## AI TOOL DECLARATION

The authors declares that no AI and related tools are used to write the scientific content of this manuscript.

## DATA AVAILABILITY

Data will be available on request

## REFERENCES

- Ahmed, S., & Rahman, M. M. (2020). Microwave imaging for biomedical applications: A review. *Biomedical Signal Processing and Control*, 62, 102094.
- Allen, S. J., Crown, S. E., & Handel, T. M. (2007). Chemokine: Receptor structure, interactions, and antagonism. *Annual Review of Immunology*, 25, 787–820.
- Andrade, M. A., & Bork, P. (2000). Automated protein modeling. *Bioinformatics*, 16, 487–499.
- Andrýsková, P., & Vrba, J. (2021). Microwave tomography for medical diagnostics. *Sensors*, 21(4), 1234.

- Arnold, S. E., Arvanitakis, Z., Macauley-Rambach, S. L., Koenig, A. M., Wang, H. Y., Ahima, R. S., ... Craft, S. (2018). Brain insulin resistance in type 2 diabetes and Alzheimer disease. *Nature Reviews Neurology*, 14(3), 168–181.
- Bachelier, F., et al. (2013). International Union of Pharmacology XXX. *Pharmacological Reviews*.
- Benket, P., Biasini, M., & Schwede, T. (2011). SWISS-MODEL. *Nucleic Acids Research*, 39.
- Biessels, G. J., & Reijmer, Y. D. (2014). Brain changes underlying cognitive dysfunction in diabetes. *Lancet Neurology*, 13(9), 978–987.
- Bourqui, J., & Fear, E. C. (2017). System for radar-based microwave imaging of the thorax. *IEEE Transactions on Microwave Theory and Techniques*, 65(9), 3451–3461.
- Butterfield, D. A., & Halliwell, B. (2019). Oxidative stress, dysfunctional glucose metabolism and cognitive decline in Alzheimer's disease. *Nature Reviews Neuroscience*, 20(3), 148–160.
- Case, D. A., et al. (2020). *AMBER 2020 reference manual*.
- Chen, Y., & Wang, G. (2016). Nonlinear inversion in microwave tomography. *IEEE Transactions on Antennas and Propagation*, 64(11), 4750–4759.
- Choi, U., & Park, H. (2019). Parkin structure–function. *Frontiers in Neuroscience*, 13.
- Cook, R. L., Householder, K. T., Chung, E. P., Prakapenka, A. V., DiPerna, D. M., & Sirianni, R. W. (2015). A critical evaluation of drug delivery from ligand-modified nanoparticles. *Journal of Controlled Release*, 220, 89–97.
- Craddock, I. J. (2018). Microwave radar for non-invasive tumor detection. *Progress in Electromagnetics Research B*, 78, 35–52.
- Dabrowski, A., et al. (2019). Machine learning in microwave imaging for cancer detection. *IEEE Access*, 7, 11236–11248.
- DeLano, W. L. (2002). *PyMOL molecular graphics system*.
- Devasena, B., Kiran Kumar, S., Anitha, W., Balaji, B., & Mahalakshmi, J. (2005). Sustainable biofuel production from fruit waste: A waste-to-energy approach. *The Bioscan*, 20(2), S2:606–609.
- DiMaio, F., et al. (2011). Protein structure prediction. *Nature*, 473.
- Duarte, A. I., Proença, T., Oliveira, C. R., & Santos, M. S. (2010). Insulin in the brain: Mechanisms and diseases. *Current Alzheimer Research*, 7(1), 3–36.
- Duarte, J. M. N. (2015). Metabolic alterations in the diabetic brain. *Neuroscience*, 309, 233–242.
- Eastman, P., et al. (2017). OpenMM MD engine. *PLOS Computational Biology*.
- Elam, D. S. (2015). MD simulation of neuro proteins. *Journal of Molecular Graphics and Modelling*.
- Fear, E. C., & Potter, M. (2022). Advances in radar-based medical imaging. *IEEE Microwave Magazine*, 23(5), 45–57.
- Fiser, A., & Šali, A. (2003). Modeller. *Methods in Enzymology*.
- Forster, R., Davalos-Misslitz, A. C., & Rot, A. (2008). CCR7 and its ligands. *Nature Reviews Immunology*, 8(5), 362–371.
- Gabriel, S., Lau, R. W., & Gabriel, C. (1996). Dielectric properties of tissues. *Physics in Medicine & Biology*, 41(11), 2231–2249.
- Ghosh, A., et al. (2021). Hyperglycemia-induced neuroinflammation. *Neuroscience*, 458, 314–326.
- Golnabi, A., et al. (2020). Microwave imaging of complex thoracic structures. *Sensors and Actuators A*, 314, 112260.
- Griffith, J. W., Sokol, C. L., & Luster, A. D. (2014). Chemokines and chemokine receptors. *Annual Review of Immunology*.
- Han, Z., Zhou, Y., & Zhou, Z. (2023). Targeted drug delivery using MOFs. *Next-Generation Nanomedicine*, 3–4, 100027.
- Hartinger, A., & Kurrant, D. (2021). Microwave-ultrasound hybrid systems. *Biomedical Physics & Engineering Express*, 7(2), 025017.
- Hornak, V., et al. (2006). Improved protein force field. *Proteins*.
- Jo, S., et al. (2014). CHARMM-GUI. *Journal of Computational Chemistry*.
- Kitada, T., et al. (1998). PARK2 and Parkinson's. *Nature*, 392.
- Kodl, C. T., & Seaquist, E. R. (2008). Cognitive dysfunction and diabetes mellitus. *Endocrine Reviews*, 29(4), 494–511.
- Kleinridders, A., Ferris, H. A., Cai, W., & Kahn, C. R. (2014). Insulin action in brain. *Diabetes*, 63(7), 2232–2244.
- Kumar, S., & Nussinov, R. (2002). Protein dynamics in disease. *Chemical Reviews*.
- Lazebnik, M., et al. (2007). Tissue dielectric properties. *Physics in Medicine and Biology*, 52(20), 6093–6115.
- Lin, C., Visco, D., Angioletti-Uberti, S., Laan, L., & Kraft, D. (2021). Direct visualization of superselective colloid-surface binding.
- Lu, B., Nagappan, G., & Lu, Y. (2013). BDNF and synaptic plasticity. *Nature Reviews Neuroscience*, 14(1), 13–27.

- Maecker, H. T., et al. (2012). Standardizing immunophenotyping. *Nature Reviews Immunology*.
- Mammen, M., et al. (1998). Polyvalent interactions. *Angewandte Chemie International Edition*, 37(20), 2755–2794.
- Meaney, P. M., et al. (2019). Clinical evaluation of microwave tomography. *Academic Radiology*, 26, 233–241.
- Murphy, P. M., et al. (2014). Chemokine receptor nomenclature. *Pharmacological Reviews*, 66(1), 1–79.
- Nafisa Farheen, S., E. Sangeetha, Devasena, B., L. Ashwini, & Geetha, N. B. (2025). Exploring medicinal plants for hepatocellular carcinoma therapy: A mini review. *The Bioscan*, 20(2), S2:590–592.
- Nikolova, N. K. (2011). Microwave imaging for medical diagnostics. *IEEE Transactions on Microwave Theory and Techniques*, 61(5), 2346–2360.
- O'Loughlin, D., et al. (2020). Portable microwave imaging devices. *Sensors*, 20(10), 2864.
- Pickering, M., Cumiskey, D., & O'Connor, J. J. (2018). Actions of TNF- $\alpha$ . *Progress in Neurobiology*, 74(4), 325–343.
- Porter, E., et al. (2016). Microwave thoracic imaging: Simulation studies. *IEEE Access*, 4, 9853–9862.
- Ramya, R., Thangasubha, T., L. Ashwini, & S. C. Subha (2025). A review on the economic impact of *Penaeus monodon* aquaculture. *The Bioscan*, 20(2), S2:534–537.
- Revathi, K., Harishkumar, B., R. Lavanya, Linisha, N. M., & Maram Soumya Sree (2025). Honey-flavoured probiotic yogurt enriched with fruit pulp. *The Bioscan*, 2020(3), S.I(3):992–995.
- Revathi, K., W. Anitha, R. Lavanya, Linisha, N. M., & M. Sudha (2025). Emerging threat of COVID-19 associated mucormycosis. *The Bioscan*, 2020(3), S.I(3):958–962.
- Rot, A., & von Andrian, U. H. (2004). Chemokines in immunity. *Nature Reviews Immunology*.
- Sarafianou, M., et al. (2022). Dielectric contrast in lung tissues. *Bioelectromagnetics*, 43(4), 293–305.
- Senthil Kumar, K. S., Senthilkumar, G. P., R. Lavanya, Linisha, N. M., & M. Sudha (2025). Emergence of green fungus. *The Bioscan*, 2020(3), S.I(3):987–991.
- Senthil Kumar, K. S., Senthilkumar, G. P., R. Lavanya, Linisha, N. M., & Paranthaman (2025). Selective cytotoxic effect of *Allium ascalonicum* extract. *The Bioscan*, 2020(3), S.I(3):980–986.
- Shea, J. D., et al. (2017). UWB radar for thoracic imaging. *IEEE Transactions on Biomedical Engineering*, 64(11), 2777–2787.
- Sindhuja, A., Shobana, S., & Geetha, N. B. (2025). Spinel SrFe<sub>2</sub>O<sub>4</sub> nanoparticles. *The Bioscan*, 20(2), S2:626–630.
- Sims-Robinson, C., Hur, J., Hayes, J. M., & Feldman, E. L. (2012). Neuronal damage in diabetes. *Journal of Alzheimer's Disease*, 30(2), S153–S165.
- Sokal, C. L., & Luster, A. D. (2015). Chemokines in innate immunity. *Cold Spring Harbor Perspectives in Biology*, 7(5), a016303.
- Srikanth, V., Sinclair, A. J., Hill-Briggs, F., Moran, C., & Biessels, G. J. (2020). T2DM and cognitive dysfunction. *Lancet Diabetes & Endocrinology*, 8(6), 436–447.
- Steniffer Jebaruby Stanly, Sent Hil Kumar G. P., Devasena, B., Linisha, N. M., & Paranthaman (2025). Activated carbon-based filtration systems. *The Bioscan*, 2020(3), S.I(3):976–979.
- Stranahan, A. M., & Mattson, M. P. (2015). Metabolic reserve and cognitive aging. *Journal of Alzheimer's Disease*, 48(1), S67–S80.
- Sung, H., et al. (2021). Global cancer statistics. *CA: A Cancer Journal for Clinicians*, 71(3), 209–249.
- Swetha, M., Kiran Kumar, K., Devasena, B., & Mahalakshmi, J. (2025). Review of mosquito management strategies. *The Bioscan*, 20(2), S2:541–543.
- Tognola, G., et al. (2020). Electromagnetic-based cancer detection. *Medical Engineering & Physics*, 78, 34–45.
- Viola, A., & Luster, A. D. (2008). Chemokines and T-cell function. *Nature Immunology*.
- Vickneswari, M., Harishkumar, B., R. Lavanya, & Nirmala, B. (2025). CT imaging and steroid therapy in COVID-19. *The Bioscan*, 2020(3), S.I(3):968–971.
- Vickneswari, M., Monish Raj, R., Vijaya Krishanan, P., Dhiva, G., & Palthagam Ganesan (2025). Mitigating *Salmonella* risks. *The Bioscan*, 2020(3), S.I(3):950–952.
- Vickneswari, M., Monish Raj, R., Vijaya Krishanan, P., Palthagam Ganesan, & Jeevitha (2025). Health and environmental concerns of antiscalants. *The Bioscan*, 2020(3), S.I(3):953–957.
- Wolf, M., & Moser, B. (2012). Antimicrobial activities of chemokines. *Nature Reviews Immunology*, 12(7), 522–532.
- Wu, Y., & Fang, Q. (2018). Review of electromagnetic imaging. *Journal of Electromagnetic Waves and Applications*, 32(7), 850–873.
- Yanagawa, Y., Mao, X., & Ishii, K. J. (2019). Chemokines in immune cell development. *Frontiers in Immunology*, 10, 1411.
- Zhang, X., & Zhang, G. (2016). Neuronal damage in diabetes. *Brain Research Bulletin*, 128, 1–6.
- Zhao, Y., et al. (2020). Integration of omics in diabetic brain research. *Journal of Translational Medicine*, 18, 35.
- Zlotnik, A., & Yoshie, O. (2012). The chemokine superfamily revisited. *Immunity*, 36(5), 705–716.

