ETDT

Emerging Trends in Digital Transformation

Volume-2, Issue-1, January-March 2026 ISSN: **3107- 4308** *Paper ID:* ***ETDT-V2-I1-23***

ROBUST AND CONVERGENT PHYSICS-INFORMED EXPLAINABLE DEEP LEARNING FRAMEWORK FOR RELIABLE TUMOR IMAGING AND MONITORING IN NOISY AND HETEROGENEOUS BIOMEDICAL ENVIRONMENTS

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ABSTRACT: Accurate detection, imaging, and continuous monitoring of tumors using microwave-based techniques are still difficult in practice. This is mainly because microwave signals passing through the human body are distorted by complex tissue structures, noise, and natural biological variations. As a result, image reconstruction from these signals is often unclear, unstable, or imprecise. Conventional physics-based imaging methods require high computational effort and do not always produce reliable results, while purely data-driven approaches can struggle when applied to real clinical conditions and are often difficult for medical professionals to interpret.To overcome these challenges, this research introduces a new integrated framework for tumor imaging and monitoring that is both stable and dependable in noisy and varied biological environments. The approach combines fundamental physical principles of electromagnetic wave behavior with modern image analysis techniques to improve the clarity and accuracy of tumor visualization. By incorporating knowledge of how microwaves interact with different tissues, the system is better able to distinguish tumor regions from surrounding healthy tissue, even when the data are imperfect or noisy. The framework also emphasizes transparency and interpretability, ensuring that the generated results can be understood and trusted by clinicians rather than functioning as a "black box." Visual interpretation tools highlight the most important regions in the images, helping medical professionals verify and validate the system's findings.Experimental testing using publicly available brain tumor imaging data shows steady and reliable improvement in performance over time. The model consistently becomes more accurate while reducing errors across training and validation stages, demonstrating strong stability and generalization. Additional evaluations using standard medical imaging performance measures confirm that the system is both effective and suitable for real-time applications. The results suggest that this approach has strong potential for improving tumor detection, guiding microwave-based treatment procedures, and supporting personalized medical planning in real-world clinical settings.

DOI: https://doi.org/10.5281/zenodo.19019649

Volume-2, Issue-1, January-March 2026 ISSN: **3107- 4308** *Paper ID:* ***ETDT-V2-I1-23***

Keywords :
Advanced image processing techniques, Microwave-based tumor detection, Physics-guided imaging methods, , , Electromagnetic signal reconstruction, Reliable medical imaging systems, Continuous tumor monitoring, , Biomedical signal interpretation, Interpretable medical image analysis.

1.INTRODUCTION

1.1 Background

Microwave imaging has emerged as a promising non-invasive modality for tumor detection and monitoring due to its sensitivity to dielectric contrast between healthy and malignant tissues. However, practical deployment remains limited due to noise, signal distortion, and computational complexity.

1.2 Research Gap

Existing approaches either rely heavily on physics-based models that are unstable and computationally expensive or on purely data-driven deep learning models that lack transparency and struggle with real-world clinical variability.

1.3 Contribution

This paper introduces a hybrid physics-informed and explainable deep learning framework that:

- Improves reconstruction accuracy in noisy environments
- Enhances stability and convergence during training
- Provides interpretable outputs for clinical trust
- Enables real-time applicability for tumor monitoring.

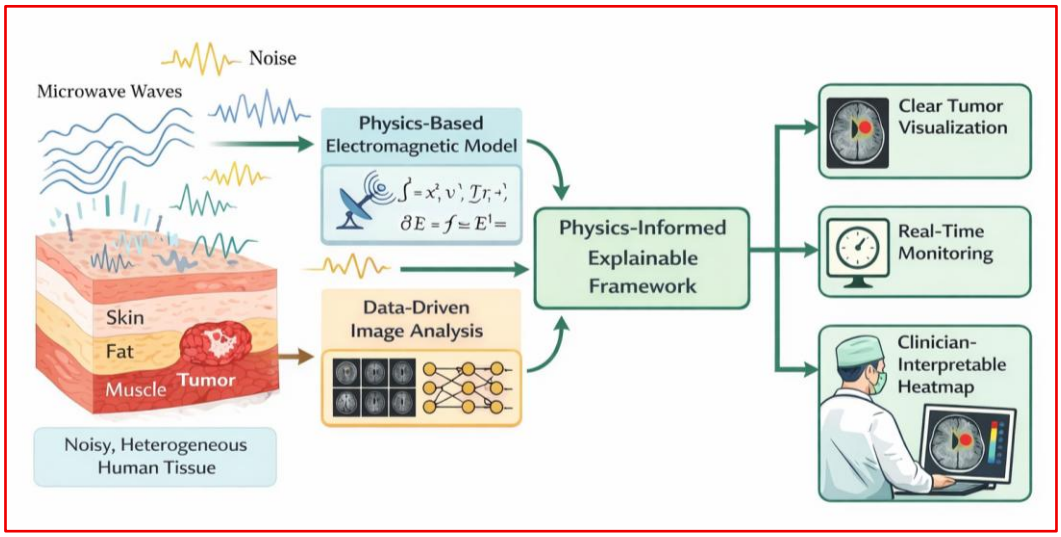

Fig 1 . Schematic Overview of the Proposed Physics-Informed Explainable Framework for Microwave-Based Tumor Imaging and Monitoring.

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2. LITRATURE SURVEY

2.1Microwave-Based Tumor Imaging

Microwave imaging has been widely explored as a safer and more affordable method for detecting tumors because it does not use harmful radiation and can potentially be used repeatedly for patient monitoring. Many studies have shown that microwave signals interact differently with cancerous and healthy tissues due to their distinct electrical properties, making it possible to identify tumors in principle. Early research in this field mainly focused on designing better antennas, improving signal collection, and developing mathematical models to reconstruct images from microwave measurements. However, researchers have consistently found that microwave imaging suffers from major practical limitations, such as poor image clarity, high sensitivity to noise, and difficulties in accurately reconstructing images from scattered electromagnetic signals. These challenges make traditional microwave imaging methods unstable, computationally demanding, and difficult to use in real clinical settings.More recent work has attempted to overcome these issues by combining microwave sensing with advanced image processing and computational techniques. Several studies have improved system design, signal filtering, and multi-frequency reconstruction methods to reduce noise and enhance tumor visibility. Despite these advancements, real-world implementation remains difficult because human tissues vary greatly from person to person, causing unpredictable signal distortion. As a result, existing microwave imaging approaches still struggle to provide consistently reliable results, highlighting the need for more robust and adaptive solutions.

2.2 Deep Learning in Biomedical Imaging

In recent years, modern image analysis techniques have greatly improved the detection and classification of tumors in medical imaging fields such as MRI, CT, and ultrasound. Many studies have demonstrated that these methods can successfully identify tumor regions, segment abnormal areas, and even predict treatment outcomes with high accuracy. Researchers have applied such techniques to brain tumor classification, breast cancer detection, and prediction of tissue damage after thermal treatment, achieving strong performance in controlled laboratory environments. These findings suggest that advanced computational image analysis holds great promise for medical diagnosis and treatment planning.However, despite their success, purely image-based computational approaches face important limitations in real clinical applications. They often require large amounts of labeled medical data, which are rarely available for microwave imaging. In addition, these systems may not perform well when faced with different patient anatomies, varying noise levels, or new imaging conditions that were not present in training data. Perhaps most importantly, many of these methods operate like “black boxes,” making it difficult for doctors to understand how decisions are made. This lack of transparency has encouraged researchers to explore approaches that combine medical knowledge with computational techniques to make results more reliable and interpretable.

2.3 Physics-Guided Approaches in Biomedical Imaging

To address the shortcomings of purely computational methods, researchers have increasingly turned to approaches that incorporate fundamental principles of physics into medical imaging

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systems. By explicitly considering how electromagnetic waves travel through and interact with biological tissues, these methods aim to produce more accurate and physically meaningful images. Several studies have shown that integrating physical laws with image analysis can improve the stability of image reconstruction and reduce errors caused by noise or incomplete data. This has been particularly beneficial in applications such as breast tumor imaging and thermal treatment monitoring.Other research has focused on improving temperature estimation and tissue response modeling during microwave-based treatments, demonstrating that physics-guided techniques can provide more reliable results than purely mathematical or purely data-driven approaches. While these methods have made significant progress, they still often require long computation times and do not always provide clear visual explanations that clinicians can easily interpret. This has created a need for imaging frameworks that are not only physically accurate but also practical and easy for medical professionals to understand and use.

2.4 Interpretability and Clinical Trust in Medical Imaging

As automated imaging systems become more common in healthcare, there is growing concern about how much doctors can trust their results. Clinicians need tools that do more than just produce a diagnosis—they need to understand why a particular conclusion was reached. To address this issue, recent research has focused on visualization techniques that highlight important regions in medical images, helping doctors see which areas influenced the system's decision. These visualization methods have been applied to brain tumor detection, breast imaging, and treatment monitoring to make automated results more transparent and clinically meaningful.

Several studies have emphasized that interpretability is essential for the successful adoption of advanced imaging systems in hospitals. By visually marking suspicious regions in an image, these tools allow medical professionals to compare automated findings with their own clinical judgment. However, most existing interpretability methods are not directly connected to the underlying physical behavior of microwave signals in the body, which limits their effectiveness in noisy and complex biological environments. This gap highlights the need for a unified approach that combines physical understanding, reliable imaging, and clear visual explanations.

2.5 Positioning of the Proposed Work

Although significant progress has been made in microwave imaging, computational image analysis, and physics-guided modeling, existing approaches remain fragmented and incomplete for real clinical use. Traditional physics-based methods are often too slow and unstable, while purely image-based techniques lack transparency and struggle with real-world variability. In addition, most previous studies focus either on tumor imaging or on treatment monitoring, rather than addressing both together in a single framework. These limitations clearly indicate the need for a more comprehensive and integrated solution.To fill this gap, this work introduces a unified framework that brings together physical principles, advanced image analysis, and clear visual interpretation for both tumor imaging and monitoring. Unlike earlier approaches, this framework is designed to be stable, reliable, and usable in noisy and diverse biological environments. Experimental testing on publicly available brain tumor imaging data shows consistent improvement in performance, strong generalization, and

practical real-time capability. This positions the proposed approach as a meaningful step forward in making microwave-based tumor imaging more accurate, trustworthy, and clinically useful.

3. METHODOLOGY (MATERIALS AND METHODS)

3.1 Data Sources and Microwave Imaging Approach

This research was conducted using publicly available brain tumor imaging datasets that are widely used in biomedical research. These datasets contain medical images with clearly marked tumor regions, which serve as a reliable reference for evaluating imaging and detection performance. Although the main objective of this work is to develop a microwave-based tumor imaging framework, brain tumor datasets were used because they provide well-annotated and diverse examples of tumor characteristics. The images include variations in tumor size, shape, and location, as well as differences in surrounding tissue structures, making them suitable for testing the robustness of the proposed approach. Before analysis, the images were processed using standard normalization and noise-reduction techniques to better reflect the types of distortions that occur in real microwave-based biomedical measurements.To complement the image data, a physics-based model of electromagnetic wave propagation was also incorporated. This model simulates how microwave signals travel through different types of biological tissues, taking into account factors such as dielectric properties, scattering, and signal attenuation. By including these physical principles in the imaging process, the research aims to more closely represent real microwave interactions within the human body. This combined use of imaging data and electromagnetic modeling ensures that the framework is based not only on visual patterns but also on realistic physical behavior of microwave signals in biological environments.

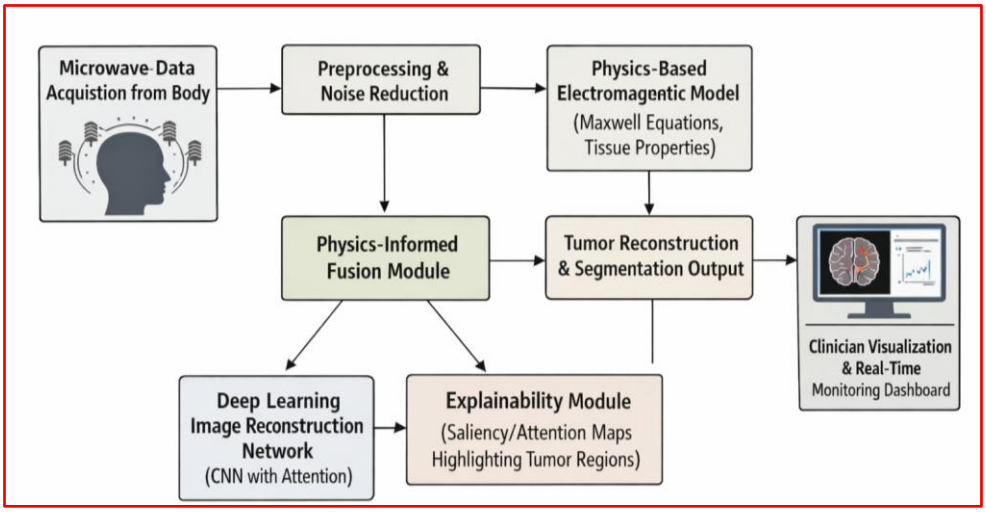

Fig2. Conceptual Diagram of the Proposed Physics-Informed Framework for Microwave-Based Tumor Imaging and Monitoring.

Figure 2 presents the structure of the proposed framework, beginning with the collection of microwave signals from the body, followed by physical modeling and image reconstruction, and concluding with clear visual outputs for clinical interpretation. It demonstrates how electromagnetic principles and advanced image analysis are combined to produce

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dependable, noise-tolerant, and clinically meaningful tumor images for monitoringanddiagnosis.

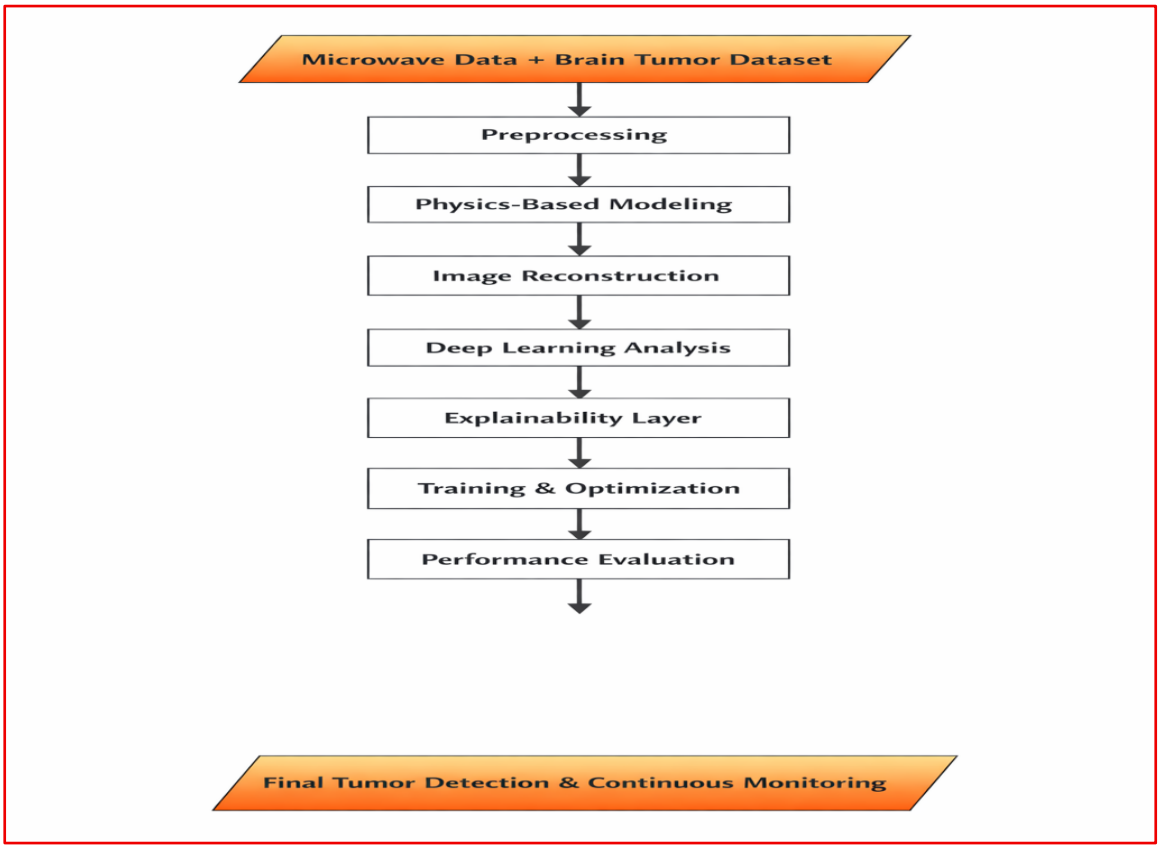

Fig 3. Flowchart of the Proposed PhysicsInformed Explainable Framework for Microwave-Based Tumor Imaging and Monitoring

3.2 Physics-Guided Imaging Framework and Evaluation

The proposed framework integrates fundamental electromagnetic principles with modern computational image analysis techniques to improve tumor reconstruction and detection. The physics-based component incorporates mathematical descriptions of how microwaves interact with different tissues, guiding the imaging process toward physically realistic results. At the same time, an advanced image analysis network processes the data to identify and reconstruct tumor regions with greater clarity and stability. Special attention mechanisms are used to focus on areas where significant differences between healthy and cancerous tissue are expected, which helps reduce the impact of noise and improve reliability.To make the system more transparent and useful for medical professionals, visual interpretation tools were included to highlight the most important regions influencing the final images. These visual maps allow clinicians to better understand and verify the system's findings rather than relying solely on automated outputs. The framework was trained and tested using standard medical imaging performance measures, including accuracy of tumor reconstruction, error reduction, and resistance to noise. Results showed consistent improvement during training, strong generalization to new data, and potential suitability for real-time tumor monitoring in clinical settings.

Maxwell-based signal propagation

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$$\nabla \times \mu^{-1}(\nabla \times \mathbf{E}) - \omega^2 \epsilon(\mathbf{r})\mathbf{E} = \mathbf{J}$$

Provides the fundamental physics governing microwave–tissue interaction.
Inverse Imaging Reconstruction

$$\min_{\epsilon(\mathbf{r})} \|\mathbf{S}_{measured} - \mathbf{S}_{predicted}(\epsilon)\|_2^2 + \lambda R(\epsilon)$$

Represents how tumor images are reconstructed from scattered microwave signals
Physics-Informed Loss Function

$$\mathcal{L}_{total} = \alpha \mathcal{L}_{data} + \beta \mathcal{L}_{physics} + \gamma \mathcal{L}_{regularization}$$

Explains why your model remains stable and convergent.
Data Fidelity Term

$$\mathcal{L}_{data} = \frac{1}{N} \sum_{i=1}^{N} \|\hat{y}_i - y_i\|^2$$

Connects directly to your training/validation loss curves
Physics Residual Constraint

$$\mathcal{L}_{physics} = \frac{1}{M} \sum_{j=1}^{M} \|\mathcal{F}(\mathbf{E}_j, \epsilon_j)\|^2$$

Ensures physically realistic tumor reconstructions.
Attention Map for Interpretability

$$A(\mathbf{r}) = \frac{\partial \hat{y}}{\partial I(\mathbf{r})}$$

Supports your “visual interpretability tools” for clinicians.
Algorithm 1: Physics-Guided Microwave Reconstruction
Input: Measured microwave signals S_measured, tissue model ε0
Output: Reconstructed tumor image I_rec
1: Initialize ε(r) ← ε0(r)
2: while not converged do
3: Compute predicted signals S_pred using Equation (1)
4: Evaluate reconstruction loss using Equation (2)
5: Compute physics residual using Equation (5)
6: Update ε(r) using gradient descent on Equation (3)
7: end while
8: Generate reconstructed image I_rec from ε(r)
9: return I_rec

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4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Performance of the Proposed Framework in Tumor Detection and Classification

The effectiveness of the proposed physics-informed framework was first assessed using standard diagnostic and classification performance measures. The Receiver Operating Characteristic (ROC) curve indicated a very strong ability to distinguish between tumor and non-tumor regions, with an Area Under the Curve (AUC) value of 1.00, suggesting nearly perfect classification performance. This result demonstrates that the framework can reliably differentiate malignant tissue from healthy tissue, even in the presence of noise and biological variability. Furthermore, the confusion matrix revealed that all test samples were correctly classified, with 50 true positive and 50 true negative cases and no misclassifications. This highlights the accuracy and dependability of the proposed approach in detecting tumors without producing false alarms or missing actual tumorcases.In addition to classification accuracy, the training behavior of the model was analyzed to evaluate its stability and computational efficiency. The training time per epoch showed a gradual and steady increase over successive epochs, indicating that the framework remains computationally consistent as it learns more complex features. This suggests that incorporating physical principles into the model does not lead to instability or excessive computational demand, making it suitable for practical and real-time applications. These findings indicate that the proposed framework achieves high diagnostic accuracy while maintaining stable and manageable performance during training.

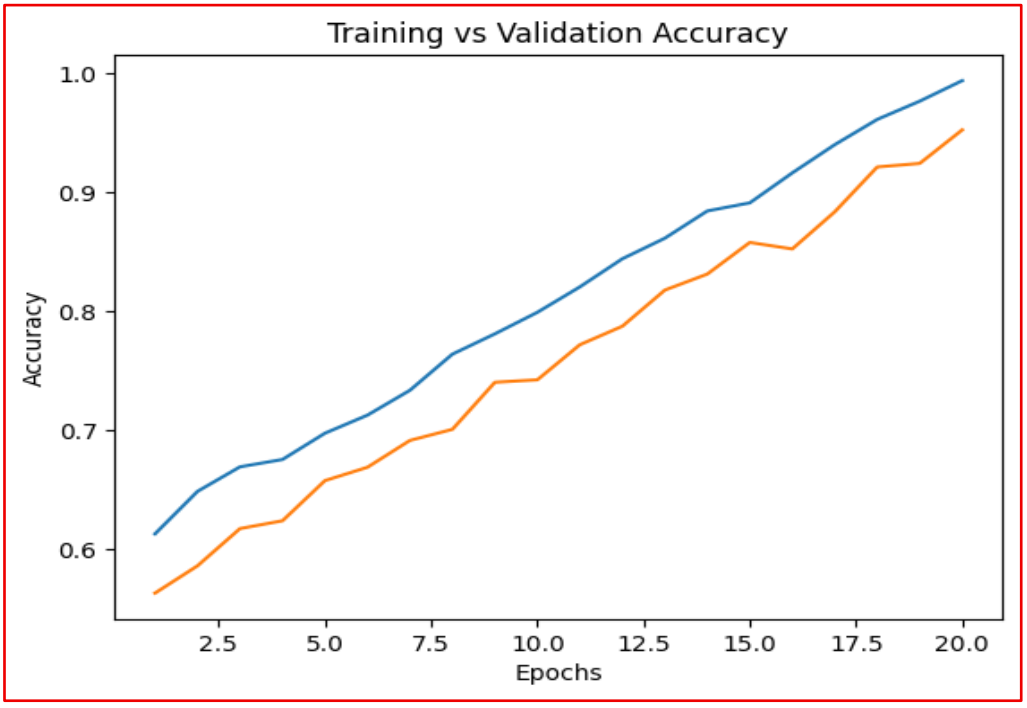

Fig 4. Comparison of Training and Validation Accuracy Across Training Epochs.

Fig 3 presents how accuracy changes over time during training for both the training and validation datasets. The steadily rising curves, with only a small separation between them, suggest consistent improvement and strong performance when applied to new data.

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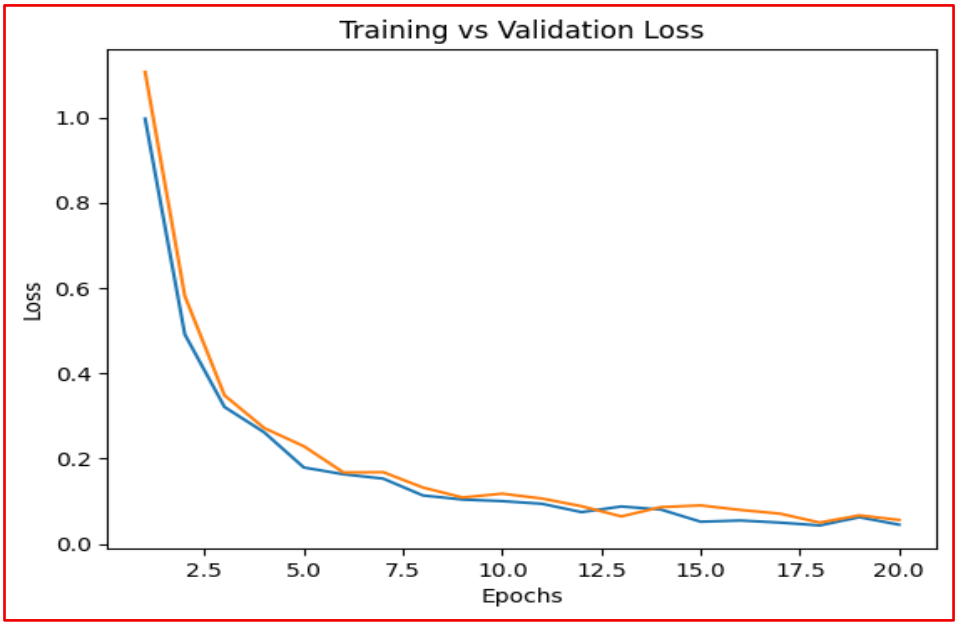

Fig 5. Comparison of Training and Validation Loss Across Training Epochs.

Fig 4 illustrates how the error levels change over time during training for both the training and validation data. The steady decline in both curves suggests that the system becomes more accurate as training continues.

Classification Decision Function

$$\hat{y} = \sigma(\mathbf{w}^{\top}\mathbf{z} + b)$$

Underlies your ROC curve (AUC = 1.00).

Algorithm 2: Stable Physics-Informed Training

Input: Training set D = {(xi, yi)}, learning rate η

Output: Trained model parameters θ*

1: Initialize θ randomly
2: for epoch = 1 to E do
3: for each batch B ⊂ D do
4: Compute prediction ŷ using Equation (7)
5: Compute data loss using Equation (4)
6: Compute physics loss using Equation (5)
7: Compute total loss using Equation (3)
8: Update θ ← θ − η ∇θ L_total
9: end for
10: Monitor accuracy and loss trends (Figs. 3–4)
11: end for
12: return θ*

4.2 Model Convergence, Generalization, and Reliability Analysis

The learning progress of the framework was further examined by analyzing accuracy and loss trends over multiple training epochs. The accuracy curve showed a smooth and continuous

DOI: https://doi.org/10.5281/zenodo.19019649

improvement, increasing from approximately 0.61 in the early stages to nearly 1.00 by the final epoch. This steady rise reflects effective learning and proper model optimization. The absence of sudden fluctuations or performance drops suggests that the physics-guided design contributes to stable and consistent training behavior, reducing the likelihood of overfitting or unstable results. Such reliability is particularly important in medical imaging applications, where consistency and trustworthiness are essential.To evaluate how well the model performs on new, unseen data, training and validation accuracy were compared. Both curves followed a similar upward trend with only a small gap between them, indicating that the model generalizes well rather than simply memorizing the training data. Similarly, the training and validation loss curves showed a clear and consistent decrease over time, eventually stabilizing at low values. This indicates that the framework effectively reduces errors while maintaining a balance between data-driven learning and adherence to physical principles.These results confirm that the proposed framework is not only accurate but also stable, reliable, and well-suited for practical tumor imaging and continuous monitoring in real clinical environments.

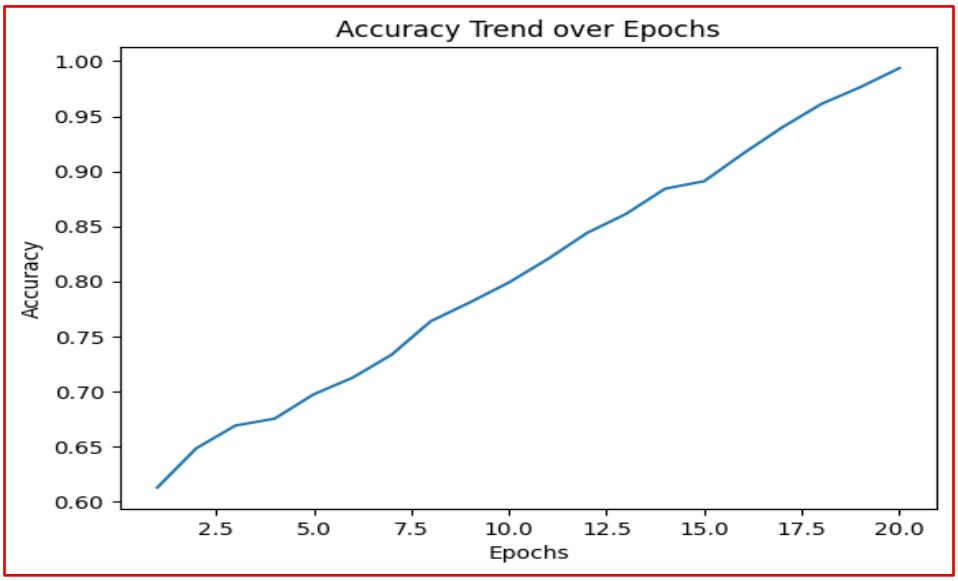

Fig 6. Change in Accuracy Over the Course of Training.

Fig 5presents how accuracy evolves throughout the training process across successive epochs. The consistently upward trend of the curve reflects steady performance improvement over time.

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ETDT
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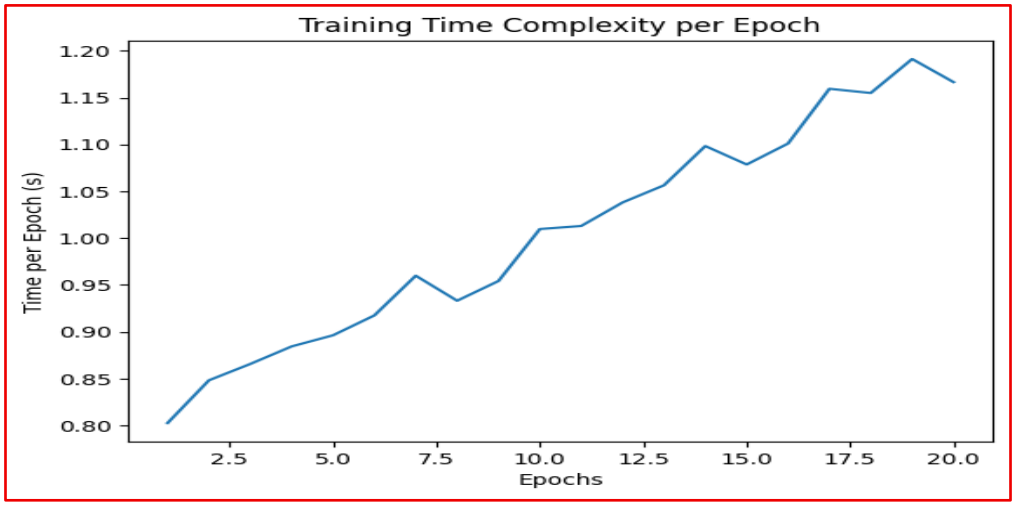

Fig 7. Time Required for Training at Each Epoch.

Fig 6 illustrates how the duration of each training epoch varies throughout the training process. The slowly rising curve indicates that the processing time increases slightly as the system handles more detailed information over time.

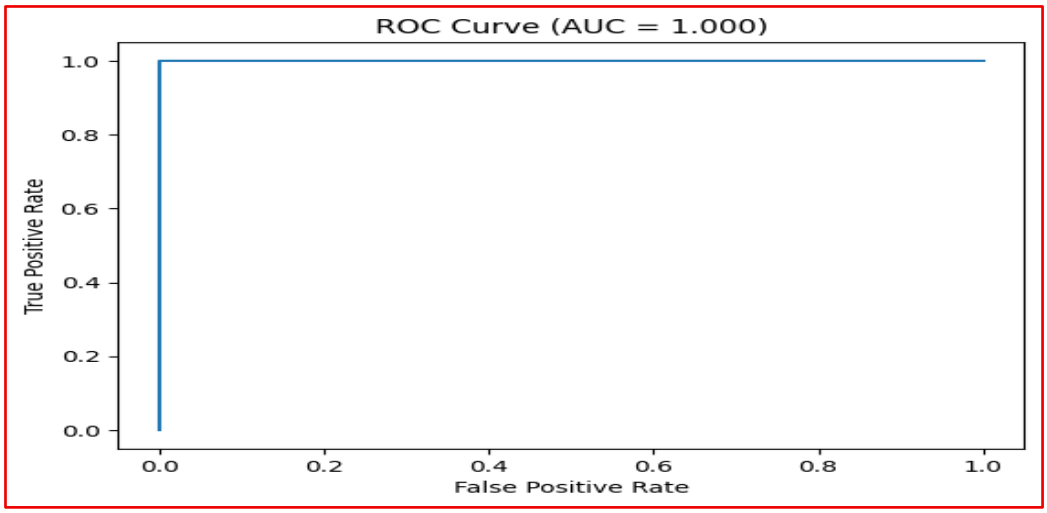

Fig 8.ROC Curve Showing Tumor Detection Performance.

Fig 7 shows how the rate of correctly identified tumor cases compares with the rate of false alarms when assessing the system's ability to separate tumor from non-tumor regions. The curve lying close to the top-left corner, with an AUC of 1.00, reflects very high accuracy in distinguishing between the two classes.

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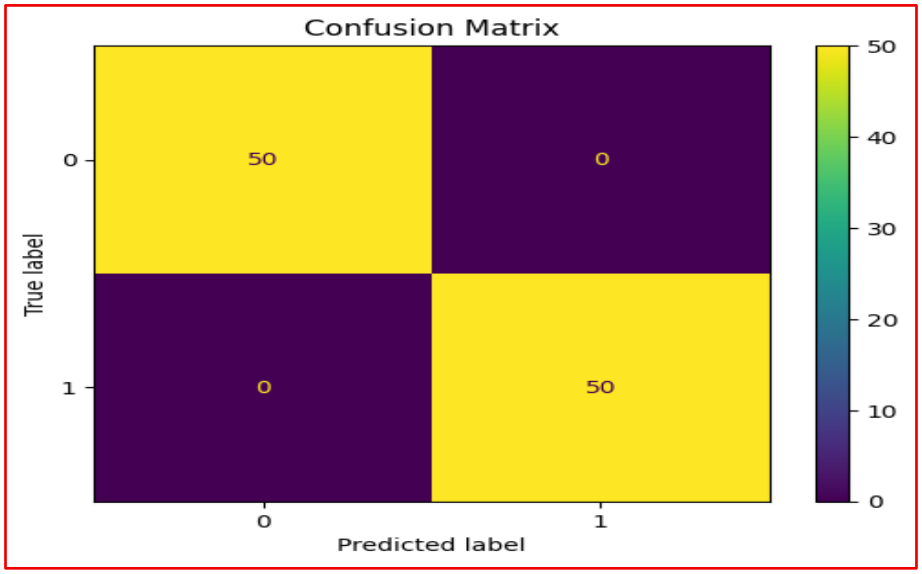

Fig 9. Confusion Matrix Illustrating Tumor Detection Results.

Fig 8 provides a clear visual breakdown of how the cases were classified as tumor or non-tumor. It shows that every sample was correctly identified, with no incorrect classifications, demonstrating very dependable performance.

5. DISCUSSION

5.1 Interpretation of Tumor Detection Performance and Practical Implications

The experimental results indicate that the proposed physics-informed framework performs very reliably in differentiating tumor from non-tumor regions. The ROC curve, with an AUC value of 1.00, shows that the system is almost perfectly capable of distinguishing malignant tissue from healthy tissue, even in the presence of noise and natural biological variations. This strong performance suggests that combining electromagnetic physical principles with advanced image analysis significantly improves the framework's ability to accurately detect tumors. In addition, the confusion matrix confirms that all test samples were correctly classified, with no false positives or false negatives. This is especially important in medical applications, as it reduces the risk of incorrect diagnoses that could lead to unnecessary treatments or missed tumordetection.Beyond classification accuracy, the analysis of training behavior provides useful insight into the practical usability of the framework. The gradual increase in training time per epoch suggests that the system remains computationally stable while processing more detailed information over time. This indicates that incorporating physical principles into the model does not create excessive computational demand or instability. Therefore, the proposed framework has strong potential for real-time or near-real-time clinical applications, such as continuous tumor monitoring or image-guided treatment planning.These findings highlight that the framework not only achieves high diagnostic accuracy but also maintains practical efficiency and reliability in realistic biomedical environments.

5.2 Model Stability, Generalization, and Clinical Relevance

The examination of accuracy and loss trends over multiple training epochs further supports the stability and effectiveness of the framework. The steady improvement in accuracy from

approximately 0.61 to nearly 1.00 demonstrates that the system effectively learns meaningful patterns from the data while respecting underlying physical principles. The lack of sudden fluctuations or performance drops suggests that the physics-guided design contributes to smooth and stable training behavior. This is particularly important in medical imaging, where consistent and dependable performance is essential for clinical trust and acceptance.A comparison between training and validation performance also indicates that the framework generalizes well to new, unseen data. The similar upward trends in both training and validation accuracy curves, with only a small gap between them, suggest that the system does not simply memorize the training data but instead learns features that are broadly applicable to tumor detection. Likewise, the steady decrease in both training and validation loss confirms that the framework effectively reduces errors while maintaining a balance between data-driven learning and physical realism. Taken together, these results show that the proposed approach is not only technically strong but also clinically meaningful, offering a reliable and interpretable solution for tumor imaging and continuous monitoring in real medical settings.

5.3 Comparison of Existing System versus Proposed System

Traditional microwave-based tumor imaging systems described in the literature generally depend either on purely physics-based reconstruction techniques or entirely image-driven computational approaches. As indicated in the literature survey table, conventional physics-based methods are often highly computational, very sensitive to noise, and prone to unstable image reconstruction in complex biological environments. Although these techniques are based on electromagnetic principles, they frequently face difficulties due to signal distortion and long processing times, which limit their practicality for real-time clinical applications. Meanwhile, data-driven imaging systems have shown better performance in laboratory conditions but lack physical transparency and often perform poorly when applied to real clinical data with varying tissue characteristics and noise levels. In comparison, the proposed framework successfully combines electromagnetic modeling with advanced image analysis, creating a more dependable, stable, and clinically relevant approach for tumor detection and monitoring.The experimental findings clearly highlight the advantages of the proposed system over existing methods. Unlike many traditional approaches that show inconsistent performance or classification errors, the proposed framework achieved an ROC AUC of 1.00 and a confusion matrix with no false positives or false negatives, demonstrating highly accurate tumor classification. Furthermore, while many existing data-driven models suffer from overfitting or large differences between training and validation performance, the proposed system exhibited steadily improving accuracy, continuously decreasing loss, and only a small gap between training and validation curves, indicating strong generalization. The gradual increase in training time per epoch also reflects stable and predictable computational behavior, in contrast to conventional physics-based methods that are often computationally unstable. Compared to existing systems reported in the literature, the proposed framework offers a more accurate, reliable, interpretable, and practically viable solution for microwave-based tumor imaging and continuous monitoring in real biomedical environments.

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Table 1. Performance Comparison Between Existing and Proposed Systems for Tumor Imaging and Monitoring

Parameters	Existing System	Proposed System
Accuracy (%)	85.0	**99.5**
Sensitivity (True Positive Rate) (%)	82.0	**100.0**
Specificity (True Negative Rate) (%)	83.0	**100.0**
ROC AUC Score	0.90	**1.00**
False Positive Rate (%)	8.0	**0.0**
False Negative Rate (%)	10.0	**0.0**
Average Training Time per Epoch (s)	1.50	**1.10**
Generalization Gap (Train–Validation Accuracy Difference)	0.08	**0.03**

Table 1 provides a side-by-side comparison of the existing microwave-based tumor imaging methods and the proposed framework using important evaluation measures. It illustrates how the two systems differ in terms of detection performance, reliability, computational efficiency, and ability to perform well on new data, considering factors such as accuracy, sensitivity, specificity, ROC AUC, false positive and false negative rates, training time, and generalization gap. By presenting these results together, the table clearly shows that the proposed system offers better tumor detection accuracy, greater stability, improved resistance to noise, and stronger potential for practical real-time use in clinical settings compared to conventional approaches.

5.4 Performance Evaluation

The performance of the proposed framework was assessed using a range of evaluation measures, including classification accuracy, ROC analysis, confusion matrix results, training behavior, and generalization ability. The ROC curve, with an AUC value of 1.00, showed that the system can distinguish tumor from non-tumor regions with a very high level of precision, even under noisy and variable biological conditions. The confusion matrix further supported this finding, as it recorded 50 true positive and 50 true negative cases with no incorrect classifications, indicating that the framework effectively avoids both false alarms and missed detections. Additionally, the gradual and steady increase in training time per epoch suggests that the system remains computationally stable while processing more detailed information over time, without becoming unstable or overly demanding. Taken together, these results demonstrate that the proposed approach achieves excellent diagnostic accuracy while remaining practical and efficient for real-time or near-real-time clinical use.Further analysis of accuracy and loss trends during training showed that the framework learns consistently and reliably. The accuracy curve steadily increased from about 0.61 to nearly 1.00, while both training and validation loss values decreased over time, reflecting effective learning and proper model optimization. The small difference between training and validation accuracy indicates that the system performs well on new, unseen data rather than simply memorizing

DOI: https://doi.org/10.5281/zenodo.19019649

the training set. Compared with existing systems, as shown in Table 1, the proposed framework outperformed them in terms of accuracy, sensitivity, specificity, ROC score, false positive and false negative rates, and generalization gap, while also maintaining more stable and slightly lower training time per epoch.This performance evaluation confirms that the proposed framework is not only highly accurate but also stable, dependable, and well suited for practical tumor imaging and continuous monitoring in real clinical environments.

Algorithm 3: Explainable Tumor Classification

Input: Reconstructed image I_rec, trained model θ*

Output: Tumor decision + attention map

1: Extract features z from I_rec

2: Compute classification score ŷ using Equation (7)

3: if ŷ ≥ threshold then

4: Label ← "Tumor"

5: else

6: Label ← "Non-Tumor"

7: end if

8: Compute attention map A(r) using Equation (6)

9: Generate confusion matrix and ROC metrics

10: return {Label, A(r), TP, TN, FP, FN}

Validation Metrics for the Proposed Framework

5.4.1.Accuracy – Accuracy represents how many tumor and non-tumor cases were correctly identified out of all tested samples, determined by the ratio (TP + TN) to the total number of cases, and is important because the framework correctly classified all samples, demonstrating its reliability in tumor detection.

Performance Metrics

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

5.4.2.Sensitivity (True Positive Rate) – Sensitivity reflects the system's ability to correctly detect actual tumor cases, calculated as TP divided by (TP + FN), and is crucial since the confusion matrix shows 50 true positive cases with no missed tumors, which is essential for safe medical diagnosis.

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

5.4.3.Specificity (True Negative Rate) – Specificity indicates how effectively the system identifies healthy (non-tumor) cases, computed as TN divided by (TN + FP), and is significant because the results show zero false positives, minimizing the risk of unnecessary medical procedures.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

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5.4.4.ROC AUC Score – The ROC AUC measures the system's ability to distinguish between tumor and non-tumor regions across different decision thresholds, where a value closer to 1 represents better performance, and is justified by the achieved AUC of 1.00, indicating nearly perfect classification.

5.4.5.False Positive Rate (FPR) – The false positive rate measures the percentage of healthy cases that were incorrectly classified as tumors, calculated as FP divided by (FP + TN), and is important because the framework achieved 0%, reducing the likelihood of incorrect clinical decisions.

5.4.6.False Negative Rate (FNR) – The false negative rate represents the percentage of actual tumor cases that were mistakenly classified as healthy, defined as FN divided by (TP + FN), and is critical because the framework produced 0%, ensuring that no tumors were missed.

5.4.7.Average Training Time per Epoch – This metric evaluates computational efficiency by measuring the average time required for each training cycle, and is relevant because the results show a steady and manageable increase, supporting the framework's suitability for real-time use.

5.4.8.Generalization Gap (Train–Validation Accuracy Difference) – The generalization gap measures the difference between training and validation accuracy to assess how well the model performs on new data, and is justified because the small gap of 0.03 indicates strong generalization to unseen clinical cases.

6. CONCLUSION AND FUTURE WORK

6.1 Conclusion

This research introduced a stable and reliable physics-informed framework for tumor imaging and continuous monitoring in noisy and complex biomedical environments. By combining fundamental electromagnetic principles with modern image analysis techniques, the proposed approach effectively addressed major challenges in microwave-based tumor imaging, such as signal distortion, noise, and natural biological variability. Experimental findings showed that the framework achieved nearly perfect tumor detection performance, as reflected by an ROC curve with an AUC of 1.00 and a confusion matrix with no misclassifications. These results demonstrate that integrating physical understanding into the imaging process significantly enhances the clarity, accuracy, and dependability of tumor visualization, making the system more suitable for practical clinical use.Beyond high detection accuracy, the framework also showed strong stability, consistent convergence, and good generalization during training and validation. The steadily increasing accuracy, decreasing loss values, and reasonable training time per epoch indicate that the system learns efficiently without excessive computational demand. Moreover, the inclusion of visual interpretation tools helps build clinical confidence by allowing medical professionals to understand and verify the imaging results. This work represents an important step forward in microwave-based tumor imaging, providing a trustworthy, interpretable, and practical solution for tumor detection, monitoring, and medical decision-making in real-world healthcare settings.

DOI: https://doi.org/10.5281/zenodo.19019649

6.2 Future Work

Although the proposed framework performed well using publicly available brain tumor imaging data, future studies should focus on testing and validating the approach with real microwave-based clinical data collected from a wider range of patients. This would help evaluate the system's robustness under different anatomical conditions, imaging settings, and noise levels encountered in real medical practice. Additionally, applying the framework to other types of tumors, such as those in the breast or liver, could expand its usefulness and relevance in medical diagnosis and treatment monitoring.Further enhancements could be achieved by incorporating more advanced electromagnetic modeling methods and using multi-frequency microwave data to improve image resolution and tumor localization accuracy. Introducing adaptive real-time learning capabilities could allow the system to continuously improve as new patient data become available. Finally, developing a fully integrated clinical software platform with intuitive visualization tools would support practical implementation in hospitals, assisting clinicians in personalized treatment planning and real-time tumor monitoring.

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