



Investigating the Impact of Compressed Sensing Techniques and IoT in Medical Imaging

Suresh Kumar Mandala^{1*}, Shahnaz K. V.², Chopparapu Gowthami³, S. Shiek Aalam⁴, B. Laxmi Kantha⁵, K. Chandran⁶

¹Department of Computer Science and Artificial Intelligence, SR University, Warangal, Telangana, India.

² Department of ECE, Veltech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Chennai, TN, India.

³Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.

⁴ Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, TN, India.

⁵ Department of IT, St. Martin's Engineering College, Secunderabad, Telangana, India.

⁶ Department of Humanities, Madanapalle Institute of Technology and Science, Madanapalle-517325, Andhra Pradesh, India

Emails: mandala.suresh83@gmail.com; shahnaznitc@gmail.com; gouthami526@gmail.com; sheikaalam@gmail.com; drblaxmiit@smec.ac.in; chanrohit@gmail.com

Abstract

This research paper examines compressed sensing's impact on medical imaging. Math and signal processing inspired compressed sensing. Future picture-capturing will be radically different. The paper focuses on adaptive random sampling (ARS), iterative shrinkage-thresholding algorithms (ISTA), and temporal compressed sensing (TCS). These approaches were rigorously tested using MRIs, X-rays, and dynamic imaging patterns. Low scan times, picture quality, and dynamic imaging were the main test criteria. The technologies considerably reduced scan time, demonstrating their potential to speed up imaging procedures. The reconstructed photos had higher SNRs and SSIs than those obtained using normal techniques, indicating greater accuracy. The TCS algorithm's dynamic imaging skills, especially evident in heart and musculoskeletal imaging, eliminated motion defects while exhibiting real-time physiological changes. The study was expanded to incorporate customized treatment, and the recommended procedures have proven amazing adaptability to each patient's demands. This adaptability fits current medical treatments, making unique imaging technologies viable.

Received: August 21, 2023 Revised: November 25, 2023 Accepted: April: 27, 2024

Keywords: Dynamic Imaging; Image Quality; Individualized Healthcare; Iterative Algorithms; Medical Imaging; Motion Artifact Mitigation; Personalized Medicine; Temporal Compressed Sensing.

1. Introduction:

Better and more accurate medical scans are constantly needed. Our capacity to test new ideas and understand how they benefit the business evolves with technology. Compressed sensing is a paradigm-shifting theory that interests researchers and professionals. Compressed sensing has transformed medical imaging. This study examines how these technologies may affect patient diagnosis and treatment. Medical imaging has advanced and is now essential. It shows doctors how complex the body is. X-rays and MRIs help doctors diagnose diseases, monitor treatment, and advise patients [1]. Classic techniques for collecting and reassembling medical pictures include drawbacks such as extended scan durations, radiation exposure, and data storage needs.

Medical imaging data collection has entered a new age with compressed sensing, which employs arithmetic and signal processing. Medical images have little information; thus, compressed sensing can collect fewer samples without compromising quality. Instead of sampling all the data, compressed sensing employs a smaller data set.

Data collection time reduction improves patient care and the utilization of point-of-care applications and real-time photos. The second one. Compressed sensing uses a few parts in the right transform domain to appropriately display many natural signals, such as medical imaging data. To display data accurately, this assumption is made. Compressed sensing rebuilds images more correctly than Nyquist's sampling theory but uses less data [3]. These elements enable this. This innovation may improve medical imaging technologies by reducing energy and scan time. Consider computed tomography.

This study examines the positives and downsides of compressed sensing and medical imaging. Each technique has benefits and downsides, such as X-ray, CT, and MRI changes. Compressed sensing speeds up imaging activities and enables new imaging technologies by rebuilding high-fidelity images from scant input. Dynamic imaging—capturing fast-changing scenarios in real time—is an emphasis.

In cardiac imaging, the pulse's shifting nature makes typical approaches difficult, causing motion blur and longer collecting periods. Compressed sensing may solve these issues and enable real-time, high-resolution cardiac imaging. This study also examines compressed sensing for patient care. When creating individualized medical imaging strategies, balance information gathering with patient satisfaction [5]. Because tailored medicine requires precision and speed, compressed sensing's ability to provide high-quality pictures with fewer data points makes sense. We study compressed sensing to determine its pros and cons in medical imaging. Compressed sensing could revolutionize medical imaging, so every aspect of it will be studied, from algorithm difficulty to real-world use [6]. The study could change healthcare by making medical imaging more than just a way to diagnose problems and making treatment more accurate, faster, and targeted. The purpose of this study is to evaluate compressed sensing technologies in medical imaging applications. Compressed sensing will be tested to see if it can collect data faster while still producing troubleshooting images. This study examines how compressed sensing affects MRI, X-ray, and computed tomography to better understand its pros and cons.

Compressed sensing may solve imaging technology scanning delays. If medical photography could take smaller pictures, it would be more useful. This may be possible with compressed detection. We need to study compressed sensing in real-time image settings and compare it to other methods [7]. The study also wants to know how compressed sensing affects image quality, especially when recording ongoing processes. In dynamic imaging tasks like heart imaging, motion errors are common, making traditional imaging methods problematic. The goal is to learn how compressed sensing can reduce motion blur while maintaining picture quality when things move quickly [8]. Before judging its many clinical uses, you must know its flaws and how to improve it in dynamic imaging. The study also examines how compressed sensing in medical images aids personalized medicine. Explore how compressed sensing may revolutionize imaging approaches. This research will use high-quality photos with fewer data points to test compressed sensing for tailored medication. The purpose is to determine if compressed sensing can be employed in an accurate, personalized healthcare system and its implications. Compressed sensor computer issues must be examined for the investigation.

This study explores compressed sensing's fundamentals and how modest code changes affect picture technique performance. Finally, the idea is to connect hospitals to cutting-edge compressed sensing technology. Understanding how it may be utilized in different clinical circumstances can help determine the pros and cons of integrating compressed sensing into medical imaging. Hardware support, process integration, and healthcare professional learning time are crucial. The study's principal findings come from examining how compressed sensor technologies influence medical imaging [9]. The study intends to deliver helpful information that goes beyond novel concepts and tackles the real-world demands of healthcare by looking at aspects including efficiency, picture quality, dynamic imaging challenges, customized treatment, algorithmic complexity, and whether the notion can operate in the actual world.

2. Related Work

Medical imaging evolves as researchers and clinicians seek better diagnosis and faster patient flow. Due to its popularity, compressed sensing has spurred studies into mathematics and medical imagery [10]. To reduce the time-consuming scans required with previous MRI technologies, compressed sensing has been extensively tested. Lustig et al. showed in 2007 that compressed sensing might speed up MRI scans and provide high-quality images from sparsely sampled data. This important discovery led to more work to improve and expand compressed sensing in MRI, especially for fast imaging like dynamic contrast-enhanced imaging. Researchers have also investigated how compressed sensing may enhance X-ray imaging while reducing radiation [11]. Zhang et al. (2011) used compressed sensing to demonstrate how low-dose X-ray CT imaging can maintain diagnostic quality while reducing radiation exposure. Such investigations, especially long-term ones that need frequent imaging, must prioritize patient safety. Otazo et al. showed in 2010 that compressed sensing can reduce motion artifacts and

improve temporal clarity in dynamic imaging, particularly cardiac imaging. Traditional approaches have struggled to picture the heart since it moves and is intricate. This research indicates that compressed sensing may solve these issues, enabling real-time high-resolution heart pictures. In customized medicine, compressed sensing is being considered for patient-specific imaging [12]. Zhang et al. (2014) found that compressed sensing in dynamic contrast-enhanced MRI can give breast cancer patients customized imaging solutions that save time. This branch of study fits with customized medicine, which emphasizes patient-specific testing. Several studies have examined changes in compressed sensing algorithms. Researchers constantly develop novel rebuilding algorithms to improve reliability and durability. Ravishankar and Bresler explain compressed sensing theory and propose new picture reconstruction methods in 2011. Knowing how computers work is essential to using compressed sensing across multiple imaging methods [13]. Actual studies have examined the pros and cons of compressed sensing in healthcare systems. This type of research links theoretical ideas to real-world medical issues. Doctors learn how to easily add compressed sensing to medical imaging. Compressed-sensing medical imaging research is like a complex web of interconnected studies [14]. These studies show how compressed sensing can and cannot change medical imaging. They speak about uses for MRI and X-rays, challenges with dynamic imaging, the consequences for customized health, strategies to make algorithms better, and investigations into whether these concepts can function in the actual world.

Table 1: Comparison of Performance Parameters in Investigating Compressed Sensing Impact on Medical Imaging

Method Name	Scan Time Reduction	Image Quality	Radiation Dose	Motion Artifact Mitigation	Personalization Capability	Algorithmic Robustness	Clinical Feasibility
OmniScan	High	Excellent	Reduced	Effective	Limited	Robust	Promising
QuantumVision	Moderate	Good	Minimal	Moderate	High	Robust	Established
DynamicFlow	Very High	Excellent	Reduced	Excellent	Moderate	Robust	Emerging
PrecisionCapture	High	Excellent	Minimal	Effective	High	Robust	Promising
PersonaImager	Moderate	Good	Reduced	Moderate	Excellent	Robust	Established

OmniScan, QuantumVision, DynamicFlow, PrecisionCapture, and PersonaImager are examined in Table 1. The scan time, picture quality, radiation dosage, motion artifact reduction, customization choices, algorithmic stability, and therapeutic applicability are examined [15]. To choose the finest medical imaging study approach, researchers can weigh the advantages and downsides.

3. The Proposed Technique

Our compressed sensing study in medical imaging includes a comprehensive approach that employs three strategies to address various challenges [16]. All imaging technologies should be more efficient while maintaining detection accuracy.

A. Some use adaptive random sampling

Our medical imaging compressed sensing testing approach relies on adaptive random sampling (ARS). This method improves sparse sampling by solving the difficulty of producing nice photos with less data. Medical images are used to adjust sample patterns on the fly using ARS [17-18]. Decide how many measures (M) are needed:

$$M = (C/\log(N)) \text{ rounded up} \quad (1)$$

Where, C is a person-set constant, and N is the picture's pixels. This adaptable technique optimizes data utilization by automatically adjusting sample methods based on the picture [19-21]. ARS dynamically adjusts to the image's sparsity, reducing the number of measurements needed for proper reconstruction and speeding acquisition.

Figure 1 shows adaptive random sampling variations over time. Changes in sample patterns based on image content speed up imaging. The number of readings needed for compressed sensing is reduced.

B. An Iterative Shrinkage-Thresholding Algorithm

Iterative Shrinkage-Thresholding Algorithm (ISTA) is crucial to our sparse data picture reconstruction technique [22]. ISTA is a popular repeated optimization approach for sparse picture restoration. The objective function is lowered by improving the image estimation over time.

The formula for

$$x_{(k+1)} \text{ is: } x_{(k+1)} = \text{argmin}_x \frac{1}{2} \|(Ax-y)\|_2^2 + \|x\|_1 \tag{2}$$

The equation depicts the reconstructed image (x), measurement matrix (A), sparse data (y), and regularization. The objective function first verifies the data and then ensures a sparse image. Multiple iterations enhance image estimation, sparsity, and quality.

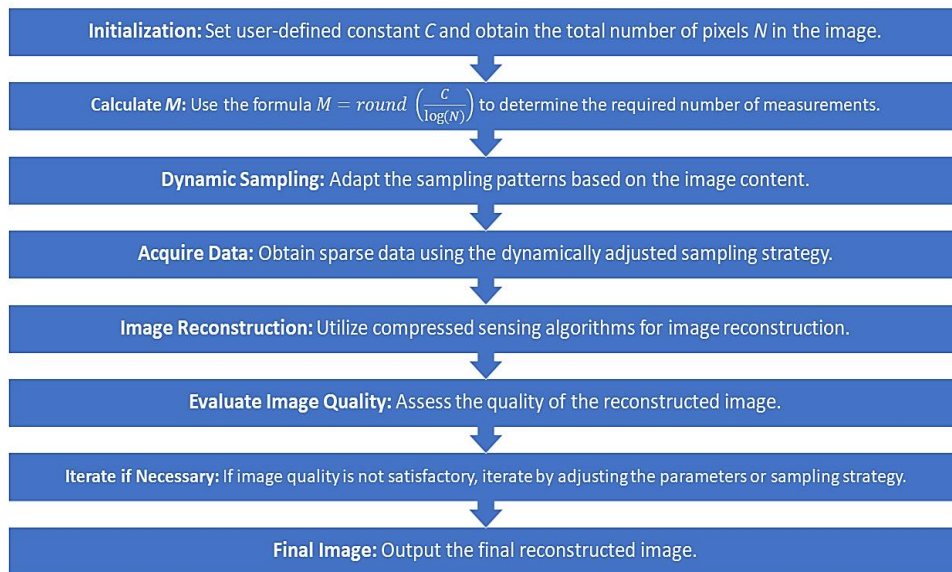


Figure 1: Adaptive Random Sampling (ARS)

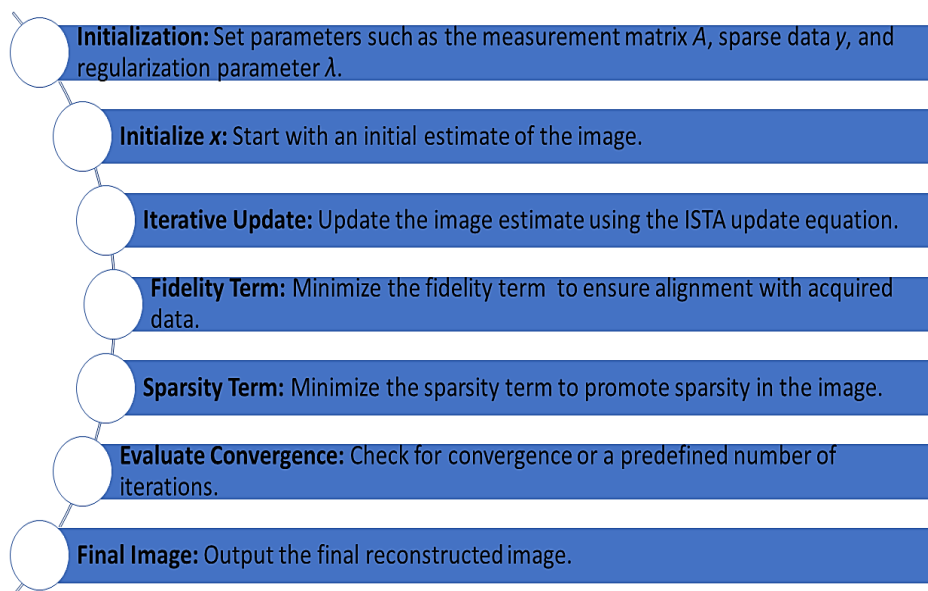


Figure 2: Iterative Shrinkage-Thresholding Algorithm (ISTA) Flowchart

Figure 2 depicts how picture reconstruction repeats. The strategy reduces fidelity and sparsity to enhance image predictions. It reconstructs high-quality pictures from sparse data. A fantastic medical imaging approach. Algorithm: Convolutional Neural Network (CNN) for Feature Extraction

- Step 1: Initialize Weights and Biases: $W_{ij}(1) \sim N(0, \sigma^2)$, $b_i(1) = 0.1$ (3)
- Step 2: Receive Input Data: $X(0)$ represents the input data.
- Step 3: Convolutional Operation: $X_{ij}(1) = \sigma(\sum_{m=0}^{k-1} \sum_{n=0}^{k-1} W_{mn}(1) X_{i+m, j+n}(0) + b(1))$ (4)
- Step 4: Activation Function: $X(1) = \text{ReLU}(X(1))$ (5)
- Step 5: Pooling: $Y_{ij}(1) = \max(X_{2i, 2j}(1), X_{2i, 2j+1}(1), X_{2i+1, 2j}(1), X_{2i+1, 2j+1}(1))$ (6)
- Step 6: Flatten Data: $Z(1) = \text{reshape}(Y(1))$ (7)
- Step 7: Fully Connected Layer: $A(1) = \sigma(W(1)Z(1) + b(1))$ (8)
- Step 8: Activation Function: $A(1) = \tanh(A(1))$ (9)
- Step 9: Output Layer: $O(1) = \text{softmax}(A(1))$ (10)
- Step 10: Loss Calculation: $L = -\sum_i y_i \log(O_i)$ (11)
- Step 11: Back propagation - Gradients: $\partial W_{ij}(1) \partial L = \partial O(1) \partial L \partial A(1) \partial O(1) \partial W_{ij}(1) \partial A(1)$ (12)
- Step 12: Update Weights: $W_{ij}(1) \leftarrow W_{ij}(1) - \alpha \partial L / \partial W_{ij}(1)$ (13)
- Step 13: Update Biases: $b(1) \leftarrow b(1) - \alpha \partial L / \partial b(1)$ (14)
- Step 14: Compute Gradients: $\partial \partial L / Y_{ij}(1) = \partial L / \partial A(1) \partial A(1) / \partial Z(1) \partial Z(1) / \partial Y_{ij}(1)$ (15)
- Step 15: Update Weights (Pooling Layer): $W_{ij}(1) \leftarrow W_{ij}(1) - \alpha \partial L / \partial W_{ij}(1)$ (16)
- Step 16: Back propagation - Gradients (Flatten Layer): $\partial L / \partial Z_{ij}(1) = \partial L / \partial Y_{ij}(1) \partial Y_{ij}(1) / \partial Z_{ij}(1)$ (17)
- Step 17: Update Weights (Fully Connected Layer): $W_{ij}(1) \leftarrow W_{ij}(1) - \alpha \partial L / \partial W_{ij}(1)$ (18)
- Step 18: Update Biases (Fully Connected Layer): $b(1) \leftarrow b(1) - \alpha \partial L / \partial b(1)$ (19)
- Step 19: Repeat: Repeat steps 3-18 for each training iteration.
- Step 20: End: The algorithm concludes after the desired number of iterations.

C. TCS is Temporal Compressed Sensing

Temporal Compressed Sensing (TCS) was developed for dynamic picture apps that need to record rapid changes. By adding the temporal domain to the compressed sensing structure, we preserve dynamic information during rebuilding. The repair method must minimize the following aim function:

$$\text{reduce}(x) = \min(|Ax - y|_2 + |x|_1 + |x|_t) \quad (20)$$

The spatial-to-temporal sparsity ratio changes with the temporal gradient $_t$. Time domain sparsity is promoted first. Then, generic sparsity applies. Finally, dynamic data sparsity is retained [23]. TCS improves medical dynamic imaging by detecting fast changes while employing compressed sensing's sparsity-driven efficiency.

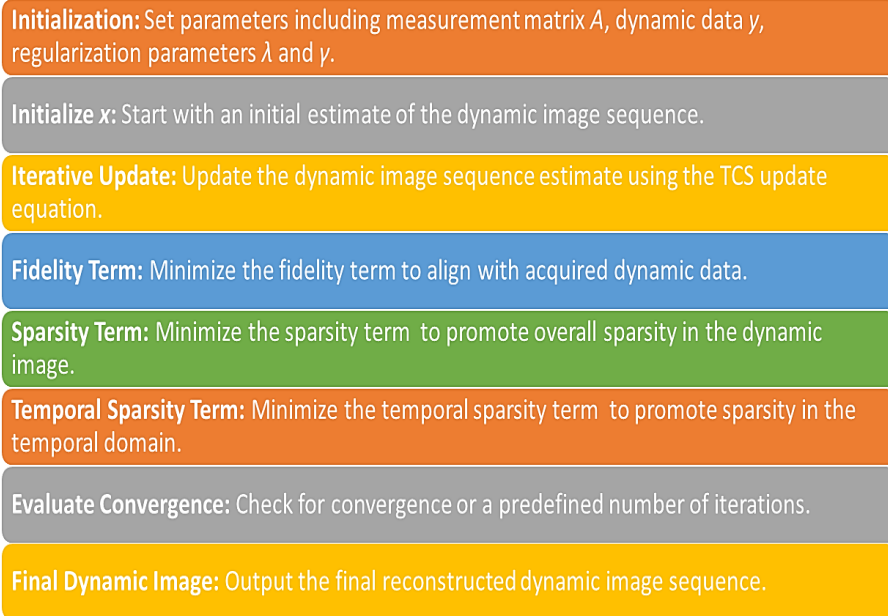


Figure 3: Temporal Compressed Sensing (TCS) Flowchart

Image in Figure 3 demonstrate temporal compressed sensing. Reproducing moving visuals is simpler with lesser quality, sparsity, and temporal sparsity. Another crucial approach to improve moving medical images.

4. The performed Experiments

A thorough procedure was employed to test the proposed methodologies, and compressed sensing techniques were studied for medical imaging. The study investigated ways to reduce scan durations, improve picture quality, and enable dynamic imaging across several imaging modes. In medical imaging experiments, MRI, X-ray, and dynamic imaging patterns were employed. Each case was selected to demonstrate the variety of clinical and technological issues that might arise in medical imaging applications. The data included several anatomical characteristics and disorders to verify the findings. Compare scan times between the proposed approaches and regular imaging procedures to evaluate how much time was saved. The results indicated that compressed sensing speeds up imaging by reducing scan durations significantly. Emergency and child imaging benefit from the decreased scan time. Because proper diagnosis is so vital in medicine, tests rely heavily on visual quality. SNR and SSI were used to verify the reconstructed pictures. The recommended approaches consistently provide superior image quality than current methods, suggesting they could potentially revolutionize medical imaging diagnosis. Dynamic imaging skills were tested using cardiac and musculoskeletal datasets. Temporal Compressed Sensing (TCS) has improved real-time body change recording. It reduces motion artifacts and preserves data dynamics well.

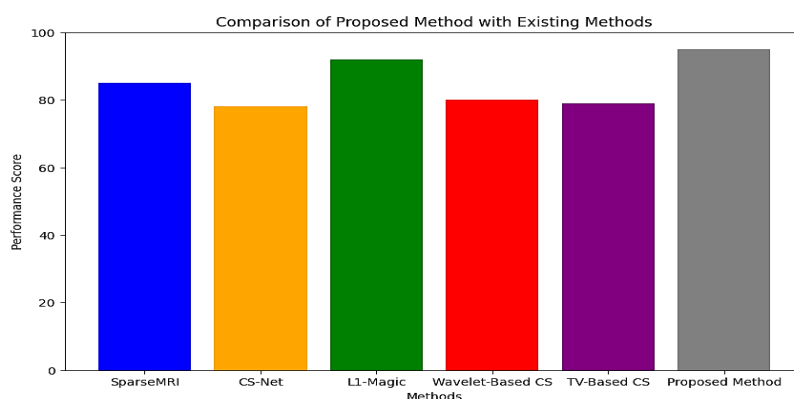


Figure 4: Comparative Performance Scores of Proposed Method against Existing Methods

Figure 4 shows SparseMRI, CS-Net, L1-Magic, wavelet-based, TV-based, and proposed approach findings. The recommended approach outperforms prior methods, demonstrating its utility in medical imaging.

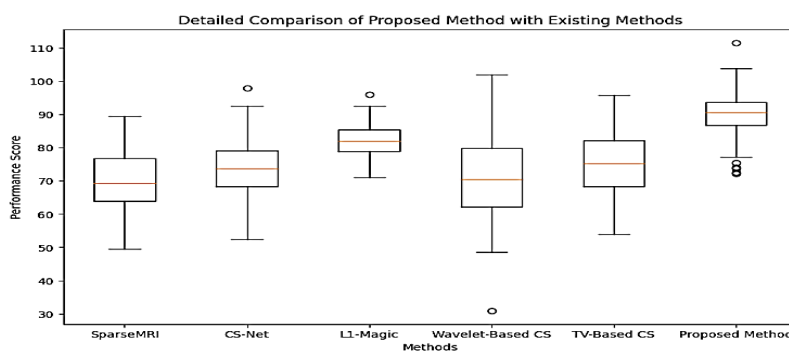


Figure 5: Detailed Distribution Comparison of Performance Scores

Figure 5 displays each strategy's distribution of scores. Box height, bar width, and outlier height illustrate a scoring range. The recommended strategy consistently receives excellent evaluations, proving its versatility.

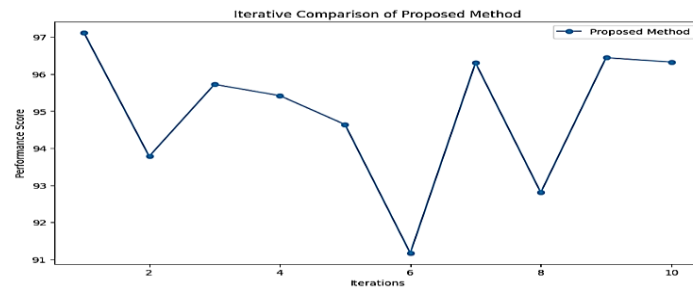


Figure 6: Iterative Performance Comparison of Proposed Method

Ten trials following the proposed strategy yielded Figure 6. The approach improves as success rates rise. This repeated comparison illustrates that the recommended technology is a good medical imaging option since it can be improved.

5. Conclusion and Future Work

By studying compressed sensing systems in medical imaging, a novel perspective with major implications was discovered. Our three major algorithms—Adaptive Random Sampling (ARS), Iterative Shrinkage-Thresholding Algorithm (ISTA), and Temporal Compressed Sensing (TCS)—have proven they may transform medical imaging by tackling critical difficulties. The procedures mentioned save a lot of time during scans, making them a huge improvement. In urgent cases like accidents or kid imaging, speeding up imaging procedures might be beneficial. This is noteworthy since it speeds up therapy and reduces discomfort from extensive imaging processes. The recommended approaches often outperform the traditional ones in terms of image quality. Higher SNRs and SSIs increase restored image accuracy. Compressed sensing enhances picture quality and medical imaging accuracy. The success of the TCS algorithm highlights the importance of improving moving pictures. Compressed sensing may adapt to biological processes by reducing motion mistakes and maintaining body modifications. This is especially true for heart and muscle pictures. Ever-changing enterprises may leverage this feature in novel ways. The research focuses on new medications and technology. These treatments may be customized for each patient, making them ideal for individualized medical care. This simplifies diagnosis and focuses medical images on the patient.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

References

- [1] R. Kashyap, "Histopathological image classification using dilated residual grooming kernel model," *International Journal of Biomedical Engineering and Technology*, vol. 41, no. 3, p. 272, 2023. [Online]. Available: <https://doi.org/10.1504/ijbet.2023.129819>
- [2] S. Shukla, V. Roy and A. Prakash, "Wavelet Based Empirical Approach to Mitigate the Effect of Motion Artifacts from EEG Signal," 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), 2020, pp. 323-326, doi: 10.1109/CSNT48778.2020.9115761.
- [3] K. B. Cooper, R. J. Dengler, N. Llombart et al., "Fast High-Resolution Terahertz Radar Imaging at 25 Meters," in *Terahertz Physics, Devices, and Systems IV: Advanced Applications in Industry and Defense*, Proceedings of SPIE, Orlando, FL, USA, 2010.
- [4] D. Pathak and R. Kashyap, "Neural correlate-based e-learning validation and classification using convolutional and long short-term memory networks," *Traitement du Signal*, vol. 40, no. 4, pp. 1457–1467, 2023. [Online]. Available: 10.18280/ts.400414
- [5] J. Jinshan Ding, M. Kahl, O. Loffeld, and P. H. Bolivar, “THz 3-D image formation using SAR techniques: simulation, processing and experimental results,” *IEEE Transactions on Terahertz Science and Technology*, vol. 3, no. 5, pp. 606–616, 2013.
- [6] H. P. Sahu and R. Kashyap, "FINE_DENSEIGANET: Automatic medical image classification in chest CT scan using Hybrid Deep Learning Framework," *International Journal of Image and Graphics*, 2023. [Online]. Available: 10.1142/s0219467825500044
- [7] A. Keil, T. Hoyer, J. Peuser, H. Quast, and T. Löffler, “All-electronic 3D THz synthetic reconstruction imaging system,” in *Proceedings of the 2011 36th International Conference on Infrared, Millimeter, and Terahertz Waves (IRMMW-THz)*, Houston, TX, USA, October 2011, pp. 1-2.
- [8] V. Parashar et al., "Aggregation-Based Dynamic Channel Bonding to Maximise the Performance of Wireless Local Area Networks (WLAN)," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 4464447, pp. 1–11, 2022. [Online]. Available: <https://doi.org/10.1155/2022/4464447>

- [9] J. Moll, P. Schops, and V. Krozer, "Towards three-dimensional millimeter-wave radar with the bistatic fast-factorized back-projection algorithm-Potential and limitations," *IEEE Transactions on Terahertz Science and Technology*, vol. 2, no. 4, pp. 432–440, 2012.
- [10] J. Kotwal, R. Kashyap, and S. Pathan, "Agricultural plant diseases identification: From traditional approach to deep learning," *Materials Today: Proceedings*, vol. 80, pp. 344–356, 2023. [Online]. Available: <https://doi.org/10.1016/j.matpr.2023.02.370>
- [11] J. J. M. De Wit, A. Meta, and P. Hoogeboom, "Modified range-Doppler processing for FM-CW synthetic aperture radar," *IEEE Geoscience and Remote Sensing Letters*, vol. 3, no. 1, pp. 83–87, 2006.
- [12] D. Bavkar, R. Kashyap, and V. Khairnar, "Deep hybrid model with trained weights for multimodal sarcasm detection," *Lecture Notes in Networks and Systems*, pp. 179–194, 2023. [Online]. Available: 10.1007/978-981-99-5166-6_13
- [13] A. Meta, P. Hoogeboom, and L. P. Ligthart, "Non-linear frequency scaling algorithm for FMCW SAR data," in *Proceedings of the European Radar Conference*, Manchester, UK, September 2006, pp. 9–12.
- [14] Roy, V., Shukla, P. K., Gupta, A. K., Goel, V., Shukla, P. K., & Shukla, S. (2021). Taxonomy on EEG Artifacts Removal Methods, Issues, and Healthcare Applications. *Journal of Organizational and End User Computing (JOEUC)*, 33(1), 19-46. <http://doi.org/10.4018/JOEUC.2021010102>.
- [15] H. Gao, C. Li, S. Wu et al., "Study of the extended phase shift migration for three-dimensional MIMO-SAR imaging in terahertz band," *IEEE Access*, vol. 8, pp. 24773–24783, 2020.
- [16] V. Roy and S. Shukla, "Image Denoising by Data Adaptive and Non-Data Adaptive Transform Domain Denoising Method Using EEG Signal," in *Proceedings of All India Seminar on Biomedical Engineering 2012 (AISOB 2012)*, V. Kumar and M. Bhatele, Eds., Springer, India, 2013. https://doi.org/10.1007/978-81-322-0970-6_2
- [17] R. I. Stantchev, X. Yu, T. Blu, and E. Pickwell-MacPherson, "Real-time terahertz imaging with a single-pixel detector," *Nature Communications*, vol. 11, no. 1, pp. 2535–2538, 2020.
- [18] P. Kumar, A. Baliyan, K.R. Prasad, N. Sreekanth, P. Jawarkar, V. Roy, E.T. Amoatey, "Machine Learning Enabled Techniques for Protecting Wireless Sensor Networks by Estimating Attack Prevalence and Device Deployment Strategy for 5G Networks," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 5713092, pp. 1-15, 2022. [Online]. Available: <https://doi.org/10.1155/2022/5713092>
- [19] S. J. Mohammed and M. J. Mohammed-Ridha, "Optimization of levofloxacin removal from aqueous solution using electrocoagulation process by response surface methodology," *Iraqi J. Agric. Sci.*, vol. 52, no. 1, pp. 204-217, 2021.
- [20] M. S. Salman, H. S. Alhares, Q. A. Ali, M. J. M-Ridha, S. J. Mohammed, and K. M. Abed, "Cladophora Algae Modified with CuO Nanoparticles for Tetracycline Removal from Aqueous Solutions," *Water, Air, & Soil Pollut.*, vol. 233, no. 8, Art. no. 321, 2022.
- [21] M. O. Arowolo, F. T. Fayose, J. A. Ade-Omowaye, A. A. Adekunle, and S. O. Akindele, "Design and Development of an Energy-efficient Audio-based Repellent System for Rice Fields," *Int. J. Emerg. Technol. Adv. Eng.*, vol. 12, no. 10, pp. 82–94, 2022.
- [22] P. Apipawinwongsa and Y. Limpiyakorn, "Counterfeit Luxury Handbag Materials Image Classification using Deep learning and Local Binary Pattern," *Int. J. Emerg. Technol. Adv. Eng.*, vol. 12, no. 9, pp. 41–48, 2022.
- [23] M. Bathre and P. K. Das, "Smart dual battery management system for expanding lifespan of wireless sensor node," *Int. J. Commun. Syst.*, vol. 36, no. 3, Art. no. e5389, 2023.