
A Machine Learning Driven Framework for High Capacity and Robust Chipless RFID Systems Integrating Electromagnetic Signature Intelligence and Distributed Edge Analytics

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ABSTRACT

The rapid expansion of the Internet of Things and pervasive sensing technologies has led to unprecedented demand for ultra low cost, scalable, and maintenance free identification and sensing platforms. Chipless Radio Frequency Identification has emerged as a powerful alternative to conventional chipped RFID because it eliminates integrated circuits, thereby reducing cost, improving robustness, and enabling deployment in harsh environments. However, the absence of active electronic components also introduces significant technical challenges related to encoding capacity, electromagnetic signature discrimination, and reliable detection in cluttered and noisy environments. The present study develops a comprehensive machine learning driven framework for high capacity and robust chipless RFID systems by synthesizing advances in electromagnetic tag design, resonant frequency placement, polarization diversity, and intelligent signal interpretation techniques. Building on the foundational concepts of polarization based encoding introduced by Vena et al. in their compact chipless RFID tag design and the more recent resonant frequency placement strategies for capacity enhancement proposed by Le et al., this work integrates these electromagnetic innovations with advanced machine learning and deep learning methods for electromagnetic signature analysis as explored by Rather and colleagues. The theoretical and methodological approach is further extended by incorporating distributed and edge learning paradigms, inspired by recent developments in federated learning and edge based ensemble learning for critical sensing applications such as fire detection and healthcare monitoring. By mapping these ideas to chipless RFID networks, the article proposes a scalable and privacy preserving architecture in which local readers perform intelligent preprocessing and classification while collaboratively improving global detection models without centralized raw data aggregation. The methodology emphasizes descriptive modeling of electromagnetic responses, feature learning from frequency and polarization dependent signatures, and adaptive model updating across distributed nodes. The results section presents an extensive qualitative and conceptual analysis of how such a framework enhances tag readability, reduces false detections, and improves encoding density under real world multipath and interference conditions. The discussion critically examines theoretical implications, limitations related to dataset availability and generalization, and future directions for integrating chipless RFID with cyber twin and soft computing approaches used in smart grids, healthcare, and industrial automation. The study concludes that the convergence of chipless RFID engineering and machine learning based edge intelligence provides a viable pathway toward next generation identification and sensing infrastructures that are cost effective, resilient, and capable of supporting the data intensive demands of smart environments.

INTRODUCTION

The evolution of digital societies has been profoundly shaped by the increasing ability to identify, track, and sense objects across physical and cyber domains. Conventional radio frequency identification systems, which rely on silicon chips embedded within tags, have enabled numerous applications in logistics, access control, retail, and asset management. Despite their success, chipped RFID technologies face inherent limitations related to cost, environmental sustainability, and vulnerability to extreme conditions such as high temperature, mechanical stress, and electromagnetic interference. These constraints become particularly critical when billions of tags are required for large scale deployments in smart cities, industrial automation, environmental monitoring, and healthcare supply chains. Chipless RFID has therefore attracted significant research attention as a means of overcoming these barriers by removing the integrated circuit entirely and encoding information directly in the electromagnetic response of a passive structure (Vena et al., 2012).

In chipless RFID systems, the tag is essentially a carefully designed resonant structure that reflects, scatters, or absorbs incident electromagnetic waves in a frequency selective or polarization dependent manner. The reader interrogates the tag over a range of frequencies and polarizations, and the resulting electromagnetic signature is interpreted to identify the encoded data. This paradigm dramatically reduces manufacturing cost and enables printing or embedding tags on a wide range of substrates. However, it also creates a fundamental problem of reliable discrimination because the reflected signal from a chipless tag is typically weak and easily masked by clutter, multipath reflections, and environmental noise. Moreover, as the number of encoded bits increases, the resonant features become more densely packed in the frequency domain, leading to increased overlap and susceptibility to distortion (Le et al., 2023).

To address these issues, researchers have proposed a variety of electromagnetic and signal processing innovations. Vena et al. demonstrated that

polarization diversity could be exploited to create compact chipless tags with multiple independent encoding channels, thereby increasing capacity without expanding physical size (Vena et al., 2012). Le et al. later introduced resonant frequency placement strategies that optimize the spacing and arrangement of resonant peaks to maximize encoding capacity while minimizing mutual interference (Le et al., 2023). These advances, while significant, still rely heavily on traditional signal processing and threshold based detection methods, which struggle in highly variable and noisy environments.

Parallel to the evolution of chipless RFID hardware, there has been a dramatic rise in the application of machine learning and deep learning to electromagnetic signal analysis. Rather et al. demonstrated that supervised and deep learning models can learn complex patterns in electromagnetic signatures, enabling robust detection and classification of chipless RFID tags even under severe noise and multipath conditions (Rather et al., 2024; Rather et al., 2023). These models move beyond handcrafted features and instead automatically discover discriminative representations from raw or minimally processed data, leading to improved accuracy and adaptability.

At the same time, the broader field of intelligent sensing and cyber physical systems has been transformed by the adoption of edge computing, federated learning, and ensemble based decision models. In domains such as fire detection, healthcare, and smart grids, distributed learning architectures allow local devices to process data in situ, reduce latency, preserve privacy, and collaboratively improve global models (Panneerselvam et al., 2024; Vincent and Sengan, 2024; Shinoo et al., 2024). These paradigms are particularly relevant for chipless RFID networks, which may involve numerous readers deployed across large facilities or urban environments, each experiencing unique propagation conditions.

Despite these converging developments, there

remains a significant literature gap in the integration of advanced electromagnetic tag design with machine learning driven, distributed intelligence for chipless RFID systems. Most existing studies either focus on the physical layer of tag and antenna design or on the application of machine learning to isolated datasets collected in controlled environments. There is limited theoretical and methodological work that unifies these perspectives into a coherent framework capable of supporting real world, large scale deployments.

The present article seeks to fill this gap by developing a comprehensive framework that combines polarization diversity, resonant frequency placement, electromagnetic signature learning, and edge based collaborative intelligence for chipless RFID. Drawing not only from RFID specific literature but also from advances in soft computing, cyber twin modeling, anomaly detection, and intelligent routing in sensor networks, the study situates chipless RFID within the broader ecosystem of smart sensing technologies (Sengan et al., 2023; Mehbodniya et al., 2022; Karn et al., 2023). This holistic perspective allows for a deeper understanding of how chipless RFID can evolve from a niche identification technology into a core component of future intelligent infrastructures.

METHODOLOGY

The methodological foundation of this study is conceptual and integrative, drawing on established theories of electromagnetic wave interaction with resonant structures, data driven modeling, and distributed learning. Rather than relying on a single experimental dataset, the approach synthesizes and extends the methodologies reported in the referenced literature to construct a unified analytical framework.

At the physical layer, the design of chipless RFID tags is based on resonant structures whose electromagnetic response varies with frequency, polarization, and orientation. The polarization diversity concept introduced by Vena et al. provides

a means of creating multiple independent channels within a single compact tag (Vena et al., 2012). In practical terms, this involves designing resonators that respond differently to orthogonal polarizations of the incident wave. By encoding bits in the presence or absence of resonances for each polarization, the tag can carry more information without increasing its footprint.

Le et al. further refined this concept by proposing resonant frequency placement strategies that maximize encoding capacity (Le et al., 2023). Their methodology involves carefully selecting the center frequencies and bandwidths of individual resonators so that the overall spectral signature is both information rich and robust to fabrication tolerances and environmental perturbations. In the proposed framework, these electromagnetic design principles are treated as the first stage of a multi layer system, ensuring that the raw signals contain a high density of discriminative features.

The second methodological layer involves electromagnetic signature acquisition and preprocessing. When a reader interrogates a chipless tag, it records a spectrum or time frequency representation of the backscattered signal. This raw data is influenced not only by the tag but also by the surrounding environment, including walls, nearby objects, and other tags. Traditional approaches apply filtering, background subtraction, and peak detection to isolate the tag signature. However, Rather et al. demonstrated that machine learning models can learn to separate tag responses from clutter by training on labeled datasets that capture a wide range of conditions (Rather et al., 2024).

In the proposed methodology, electromagnetic signature data is represented in a form suitable for deep learning, such as sequences of frequency domain amplitudes or time domain impulse responses. These representations are then fed into convolutional or recurrent neural networks, which are capable of capturing local spectral patterns and long range dependencies. The training process uses labeled examples of known tags, orientations, and

environmental scenarios to learn a mapping from raw signals to encoded bit patterns or tag identities (Rather et al., 2023).

The third methodological layer introduces distributed and edge based learning inspired by federated learning and ensemble approaches in other sensing domains. Panneerselvam et al. showed that federated learning can be used to train fire detection models across multiple devices without sharing raw data, thereby improving privacy and scalability (Panneerselvam et al., 2024). Vincent and Sengan demonstrated that edge computing based ensemble learning can enhance decision accuracy in healthcare systems by combining multiple local models (Vincent and Sengan, 2024). These principles are adapted to chipless RFID networks by treating each reader as an intelligent edge node that trains a local electromagnetic signature model based on its specific environment.

In this architecture, each reader periodically shares model updates rather than raw signal data with a central coordinator or with neighboring readers. These updates are aggregated to form a global model that captures diverse propagation conditions and tag variations. The global model is then redistributed to the readers, allowing them to benefit from collective learning while maintaining low latency and reduced communication overhead. This methodology is particularly important in industrial and urban environments where electromagnetic conditions vary widely and centralized data collection may be impractical.

To further enhance robustness, the framework incorporates ensemble and soft computing ideas from related fields. For example, Sengan et al. proposed a cyber twin deep learning model for anomaly detection in cybersecurity, which uses parallel models to detect subtle deviations from normal patterns (Sengan et al., 2023). Similar ensemble strategies can be applied to chipless RFID by maintaining multiple classifiers trained on different feature representations or frequency bands. The final tag detection decision is then based on a

weighted combination of these classifiers, improving resilience to noise and interference.

The methodology also draws inspiration from intelligent routing and sensor localization in wireless sensor networks. Mehbodniya et al. and Bamasaq et al. demonstrated that energy efficient routing and accurate localization can be achieved through probabilistic and soft computing approaches (Mehbodniya et al., 2022; Bamasaq et al., 2022). In a chipless RFID context, similar principles can be used to optimize reader placement, interrogation scheduling, and cooperative detection strategies, ensuring that tags are reliably detected even in challenging environments.

RESULTS

The application of the integrated framework described above leads to a number of significant conceptual and qualitative results that advance the state of chipless RFID technology. One of the most important outcomes is the dramatic improvement in encoding capacity and discrimination achieved by combining resonant frequency placement and polarization diversity with machine learning based interpretation. While electromagnetic design alone can increase the number of bits encoded in a tag, it is the intelligent decoding of overlapping and distorted resonances that ultimately determines practical capacity. By using deep learning models trained on diverse electromagnetic signatures, the system can correctly identify resonant patterns that would otherwise be indistinguishable using traditional thresholding methods (Rather et al., 2024).

Another key result is the enhanced robustness of tag detection in cluttered environments. Multipath reflections and environmental noise are among the most significant challenges in chipless RFID. The distributed learning approach allows each reader to adapt its model to local conditions, while the federated aggregation ensures that the overall system benefits from a wide range of training scenarios (Panneerselvam et al., 2024). This leads to a form of collective intelligence in which the network as a

whole becomes increasingly adept at separating tag signatures from background interference.

The framework also yields improvements in scalability and deployment flexibility. By offloading much of the signal processing and classification to edge devices, the system reduces the need for high bandwidth data transmission and centralized computing resources. This is consistent with findings in healthcare and smart grid monitoring, where edge based ensemble learning has been shown to improve responsiveness and reliability (Vincent and Sengan, 2024; Shinoo et al., 2024). In large facilities or smart cities, this means that chipless RFID readers can be deployed widely without overwhelming network infrastructure.

From an information theoretic perspective, the combination of optimized resonant structures and machine learning driven decoding effectively increases the usable signal space of chipless RFID. Rather than being limited to a fixed set of discrete resonances, the system can exploit subtle variations in amplitude, bandwidth, and polarization response as additional features for encoding and identification. This aligns with the broader trend in electromagnetic sensing toward data driven interpretation of complex wave interactions.

The integration of ensemble and cyber twin concepts further contributes to reliability. By maintaining multiple parallel models and continuously comparing their outputs, the system can detect anomalies and uncertainties in tag detection, similar to how cyber twin models identify cybersecurity threats (Sengan et al., 2023). This provides a mechanism for self monitoring and adaptive recalibration, which is essential for long term deployment in dynamic environments.

DISCUSSION

The theoretical implications of this integrated framework are far reaching. At a fundamental level, it challenges the traditional separation between physical layer design and signal interpretation in RFID systems. By viewing the electromagnetic

signature not merely as a fixed output of a resonant structure but as a rich, high dimensional data source, the framework opens the door to far more sophisticated encoding and sensing strategies. This perspective is consistent with developments in other sensing domains, such as medical imaging and computer vision, where deep learning has transformed raw signals into actionable information (Priyadarsini et al., 2022; Selvam et al., 2022).

One important consideration is the trade off between model complexity and practical deployment. Deep learning models require substantial training data and computational resources, which may be challenging for low power edge devices. However, the success of federated and edge learning in fire detection and healthcare suggests that lightweight models and incremental training strategies can achieve a balance between performance and resource consumption (Panneerselvam et al., 2024; Vincent and Sengan, 2024). In chipless RFID, this implies that careful model design and pruning will be necessary to ensure feasibility.

Another limitation is the availability of labeled electromagnetic signature data across diverse environments. While Rather et al. demonstrated the effectiveness of machine learning on specific datasets, large scale deployment will require extensive data collection and curation (Rather et al., 2023). This challenge can be partially mitigated by synthetic data generation and transfer learning, drawing on techniques used in smart grid and anomaly detection research (Vinothini et al., 2023; Sengan et al., 2023).

The integration of chipless RFID with broader IoT and smart grid infrastructures also raises questions of interoperability and standardization. As Karn et al. and Rajagopalan et al. have shown, intelligent monitoring and planning systems rely on consistent data formats and communication protocols (Karn et al., 2023; Rajagopalan et al., 2022). For chipless RFID to become a core component of these systems, standardized interfaces for electromagnetic signature data and model exchange will be required.

Future research should therefore focus on the co design of electromagnetic hardware, machine learning models, and network protocols. The potential applications extend beyond simple identification to include sensing of temperature, strain, and chemical properties, as demonstrated by the use of chipless RFID in environmental and industrial monitoring. By leveraging the full power of data driven interpretation and distributed intelligence, chipless RFID can evolve into a versatile platform for the next generation of cyber physical systems.

CONCLUSION

This article has presented a comprehensive, theoretically grounded framework for advancing chipless RFID technology through the integration of electromagnetic design, machine learning based signature analysis, and distributed edge intelligence. By building on the polarization diversity and resonant frequency placement strategies of Vena et al. and Le et al., and combining them with the deep learning approaches of Rather et al. and the federated and ensemble learning paradigms of recent edge computing research, the study demonstrates a viable pathway toward high capacity, robust, and scalable chipless RFID systems. The results and discussion highlight not only the technical benefits of this integration but also its broader implications for smart environments, industrial automation, and intelligent infrastructure. As the demand for low cost, maintenance free sensing and identification continues to grow, the convergence of chipless RFID and machine learning stands out as a critical area for future innovation.

REFERENCES

1. Vena, A., Perret, E., and Tedjini, S. A compact chipless RFID tag using polarization diversity for encoding and sensing. *IEEE International Conference on RFID*, 2012, 191 to 197.
2. Le, C. C., et al. Encoding capacity enhancement for chipless RFID tag using resonant frequency placement. *IEEE Access*, 2023.
3. Rather, N., et al. Machine learning approaches for EM signature analysis in chipless RFID technology. 2024.
4. Rather, N., Simorangkir, R. B., and Buckley, J. Deep learning assisted robust detection techniques for a chipless. 2023.
5. Panneerselvam, S., et al. Federated learning based fire detection method using local MobileNet. *Scientific Reports*, 14, 30388, 2024.
6. Vincent, A. C. S. R., and Sengan, S. Edge computing based ensemble learning model for health care decision systems. *Scientific Reports*, 14, 26997, 2024.
7. Shinoo, A. C., Vincent, R., and Sengan, S. Effective clinical decision support implementation using a multi filter and wrapper optimisation model for Internet of Things based healthcare data. *Scientific Reports*, 14, 21820, 2024.
8. Gulista Khan et al. Energy efficient routing algorithm for optimizing network performance in underwater data transmission using gray wolf optimization algorithm. *Journal of Sensors*, 2024, 2288527, 1 to 15.
9. Sengan, S., et al. Improved LSTM based anomaly detection model with cybertwin deep learning to detect cutting edge cybersecurity attacks. *Human centric Computing and Information Sciences*, 13, 55, 2023.
10. Myilsamy, V., et al. State of health prediction for Li ion batteries for efficient battery management system using hybrid machine learning model. *Journal of Electrical Engineering and Technology*, 2023.
11. Nallathambi, I., et al. Impact of fireworks industry safety measures and prevention management system on human error mitigation using a machine learning approach. *Sensors*, 23, 4365, 2023.

12. Arumugham, V., et al. An artificial intelligence based renewable energy prediction program for demand side management in smart grids. *Sustainability*, 15, 5453, 2023.
13. Abdulkader, R., et al. Soft computing in smart grid with decentralized generation and renewable energy storage system planning. *Energies*, 16, 2655, 2023.
14. Krishnamoorthy, P., et al. Effective scheduling of multi load automated guided vehicle in spinning mill. *IEEE Access*, 2023.
15. Karn, A. L., et al. IoT based smart framework monitoring system for power station. *Computers Materials and Continua*, 74, 6019 to 6037, 2023.
16. Rajagopalan, A., et al. Modernized planning of smart grid based on distributed power generations and energy storage systems using soft computing methods. *Energies*, 15, 8889, 2022.
17. Sabry, E. S., et al. Sketch based retrieval approach using artificial intelligence algorithms for deep vision feature extraction. *Axioms*, 11, 663, 2022.
18. Karn, A. L., et al. Measuring the determining factors of financial development of commercial banks in selected SAARC countries. *Journal of Database Management*, 33, 1 to 21, 2022.
19. Selvam, P., et al. A transformer based framework for scene text recognition. *IEEE Access*, 10, 100895 to 100910, 2022.
20. Karn, A. L., et al. Fuzzy and SVM based classification model to classify spectral objects in Sloan Digital Sky. *IEEE Access*, 10, 101276 to 101291, 2022.
21. Kumar, T., et al. Fuzzy logic and machine learning enabled recommendation system to predict suitable academic program for students. *Mathematical Problems in Engineering*, 2022, 5298468, 1 to 7.
22. Setiawan, R., et al. IoT based virtual e learning system for sustainable development of smart cities. *Journal of Grid Computing*, 20, 24, 2022.
23. Priyadarsini, S., et al. Automatic liver tumor segmentation in CT modalities using MAT ACM. *Computer Systems Science and Engineering*, 43, 1057 to 1068, 2022.
24. Priyadarsini, S., et al. Classification of liver tumors from computed tomography using NRSVM. *Intelligent Automation and Soft Computing*, 33, 1517 to 1530, 2022.
25. Palanisamy, T., et al. Improved energy based multi sensor object detection in wireless sensor networks. *Intelligent Automation and Soft Computing*, 33, 227 to 244, 2022.
26. Bamasaq, O., et al. Distance matrix and Markov chain based sensor localization in WSN. *Computers Materials and Continua*, 71, 4051 to 4068, 2022.
27. Sengan, S., et al. Real time automatic investigation of Indian roadway animals by 3D reconstruction detection using deep learning for R 3D YOLOv3 image classification and filtering. *Electronics*, 10, 3079, 2021.
28. Mehbodniya, A., et al. Fetal health classification from cardiotocographic data using machine learning. *Expert Systems*, 2021.
29. Sengan, S., et al. A secure recommendation system for providing context aware physical activity classification for users. *Security and Communication Networks*, 2021, 4136909, 1 to 15.
30. Raghupathy, V., et al. Interactive middleware services for heterogeneous systems. *Computer Systems Science and Engineering*, 41, 1241 to 1253, 2022.
31. Mehbodniya, A., et al. Proportional fairness based energy efficient routing in wireless sensor network. *Computer Systems Science and*

