Machine Learning Approaches for EM Signature Analysis in Chipless RFID Technology

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***Abstract*—In this paper, for the first time, we provide a comprehensive review of Machine Learning (ML) approaches in Chipless Radio Frequency Identification (CRFID) technology, which is a fast-developing sector with applications in inventory management, anti-counterfeiting, health monitoring, and environmental monitoring, to name a few. ML techniques are rapidly being integrated to improve CRFID systems' capabilities for robust detection of information. The combination of ML with CRFID technology is presented, examining various ML approaches, applications, challenges, and future perspectives. It is observed that ML has been successfully deployed in CRFID with high accuracy in the detection of information from CRFID tags. Challenges, such as data quality, security, and scalability are identified. Moreover, the literature currently struggles in the application of ML models on high-capacity tags, and lacks standardized data collection and sharing methodologies. We suggest the development of common data collection protocols, data sharing initiatives, and collaboration to establish a cohesive framework for CRFID data-driven research.**

***Index Terms*—Chipless RFID, Deep Learning, Electromagnetics, Machine Learning, Radar Cross Section, RFID.**

I. Introduction

The need for efficient and versatile wireless identification and sensing systems has grown immensely in today's interconnected world. Passive Chipless Radio Frequency Identification (CRFID) technology emerges as a promising solution [1]. Unlike traditional RFID systems that rely on integrated circuits (IC) on the tag antenna for data modulation and storage, CRFID systems do not require an IC or microchip. Instead, these are antenna-enabled encoders and sensors that utilize the distinctive EM responses of the tag antenna when illuminated by an EM field from a reader. The reflected EM signals are further analyzed by the reader to decode the information stored in the tag (Shown in Fig. 1) [2].

Due to the dependency on backscattered EM waves to the reader for data retrieval, CRFID systems face challenges in accuracy, data processing, and adaptability to real-world scenarios. Machine Learning (ML), a subset of Artificial Intelligence (AI), has emerged as a powerful tool to address these challenges. The ML algorithms can process large datasets, recognize patterns in data, extract valuable information from noisy signals, and adapt to dynamic environments, making them an ideal complement to CRFID technology. In this paper, for the first time, we provide a comprehensive review of the integration of ML techniques with CRFID systems, which is an emerging field enabling robust CRFID systems. We explored the different ML approaches employed, their applications, the existing challenges, and potential future directions for research and development. To streamline the review process, specific keywords were employed: "machine learning," "deep learning," and "AI," in combination with "chipless RFID". To identify relevant literature, the following search strings were utilized:

- intitle:"machine learning" OR intitle:"deep learning" OR intitle:"AI" AND intitle:"chipless".
- intitle:"AI" OR intitle:"Artificial Intelligence" OR intitle:"machine learning" OR intitle:"deep learning" AND intitle:"chipless RFID".
- "machine learning" OR "deep learning" OR "AI" AND intitle:"chipless".

The searches were conducted on IEEE Xplore and Google Scholar search engines. The initial search yielded 179 papers, which were subsequently refined based on their titles and abstracts. Out of these, 40 papers were shortlisted and then screened based on their full text, with the primary objective of identifying those that had not only mentioned ML but also implemented and validated it within the context of CRFID. After eliminating duplicates and ensuring alignment with the criteria, 13 papers were included in this review, as shown in Table I.

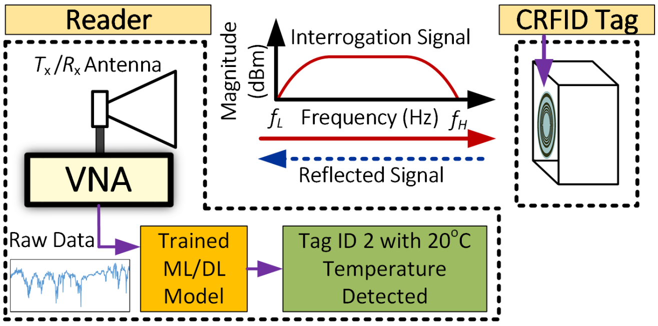

Fig. 1. Overview of an ML-assisted Chipless RFID System.

II. Chipless RFID Technology

The key components of a CRFID system include a tag and a reader (shown in Fig. 1). The tag consists of resonators,

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substrate materials, sensing materials etc., which are passive elements that interact with incident EM waves to produce unique responses. The reader consists of reader antennas, which are used to transmit and receive EM signals to and from CRFID tags [3].

Further, it consists of a signal processing unit to extract meaningful data from the EM responses. Utilizing the key components, information encoding and decoding in CRFID primarily employ two techniques: Frequency Domain (FD) and Time Domain (TD) approaches. In the FD method, information is encoded by manipulating tag antenna resonant frequencies or spectral characteristics, and the reader analyzes the frequency response of the tag using backscattered EM waves. In contrast, TD approaches focus on temporal characteristics by modulating time delays or phase shifts in the tag's response to the reader's signal.

Various signal processing methods like short-time Fourier transform (STFT) [4], wavelet-based techniques [5], threshold-based detection [6], moving average with threshold detection [7], and signal space representation (SSR) [8] have been used to identify data in CRFID systems. However, these approaches face challenges in providing consistent results across diverse tag designs, encoding methods, and configurations, requiring specific hardware, antennas, or signal processing algorithms for accuracy.

To simplify reader complexity, some studies have employed ML and Deep Learning (DL) for pattern recognition, effectively detecting EM signatures and retrieving accurate tag information [9]–[21]. Compared to conventional signal processing methods, ML/DL offers a more flexible and adaptable solution. ML/DL algorithms can learn and adapt to different encoding techniques without rule-based programming or hardware modifications, analyzing complex patterns and relationships within CRFID data. They can also handle variations in signal strength, noise, and interference, leading to improved detection and identification accuracy.

III. Machine Learning in Chipless RFID

ML involves the development of models that can identify patterns and relationships within datasets, enabling predictions, classifications, and decision-making. Based on the learning methods, ML can be broadly categorized into supervised, unsupervised, and reinforcement learning. In supervised learning, models are trained on labelled data, meaning that the input data is paired with corresponding output labels. This enables the model to learn to make predictions or classifications based on the provided examples. Unsupervised learning deals with unlabeled data, where the model aims to learn the hidden patterns and structures within the data, often through techniques like clustering and dimensionality reduction. Reinforcement learning, on the other hand, focuses on training agents to make sequences of decisions to maximize a cumulative reward.

The DL method is a facet of ML which is characterized by the use of artificial neural networks (ANN) with multiple layers, often referred to as deep neural networks. As compared to conventional ML models, which require custom feature extraction and selection from the data [22], these networks work using interconnected nodes (neurons) that process and transform data. The depth of these networks enables them to automatically extract hierarchical features from raw data, making them well-suited for handling complex tasks [23].

The complex nature of CRFID EM signals, characterized by their diverse patterns used for data encoding, requires advanced algorithms that can decode and interpret the ID or sensing points accurately. The ML/DL algorithms can be trained to recognize these specific patterns in the tag responses, enabling accurate identification of data. For instance, in the work presented in [9], a system operating in the 57-64 GHz frequency range was designed to recognize alphanumeric characters. The characters were developed using square-shaped building blocks and utilized to form a five-letter alphanumeric combination that can then reflect EM signals in different patterns. In this study, several ML models were utilized to evaluate their performance by analysing the RCS of the tags. It is shown that a Subspace k-Nearest Neighbor (kNN) Ensemble model achieved the highest accuracy at approximately 96% when classifying two alphanumeric combinations representing two IDs. Building on this work, the authors extend their work delving into DL techniques in [19]. A novel combined decoding method was introduced, incorporating both image-based decoders and DL. By utilizing a continuous-wave side-looking radar (CW-SLAR) method to generate the image and a 2D virtual representation of the frequency response, they utilize a double verification process, ensuring high reliability. A 2D Convolutional Neural Network (CNN) was trained using a dataset from 27 tags in three different positions, achieving a tag classification accuracy of 99.9%. A similar study in [14] used the 1-12 GHz frequency range to encode responses from 28 Arabic letters. The data was acquired through EM simulation using CST and classified using a Bi-long-short-term memory network (Bi-LSTM) with an accuracy of 89%.

In [11], authors propose a gesture recognition system using a CRFID tag with Split Ring Resonators (SRR) to create eight different EM signatures. The CRFID tags are designed to operate in a 3-5.5 GHz band. An Artificial Neural Network (ANN) was trained and used to detect eight responses from the tag. The authors show approximately 100% accuracy in the predicted outcomes of the ANN models. Furthermore, in [12], a retransmission-based CRFID tag operating in the 1-10 GHz range was developed using stub resonators. The authors designed the tag to encode two IDs and create a measured dataset of 816 EM signals. The study achieved a 94.4% classification accuracy using a Support Vector Machines (SVM) model. Similarly, in [10], authors utilise an RCS-based CRFID tag with concentric rings to create two IDs. The two IDs were utilized to differentiate between two types of plastics in a recycling chain. An ML model based on Random Forest (RF) was utilized to achieve accuracies between 60-75% for non-homogeneous plastic bales and 90% for homogeneous ones.

The authors also leveraged this concentric rings design in [15] to create four IDs within the 2-3.5 GHz frequency range. After evaluating various ML models, the highest accuracy of

99.6% was achieved using kNN models. The work in [16] operating in the 1.5-5 GHz range utilized concentric ring design to create and identify 16 different IDs. Their model combined Principal Component Analysis (PCA) with Logistic Regression (LR) and probability studies, achieving accuracy rates within the range of 95-100%.

In [13], C-shaped structures overlapped to form an array of "E" shaped structures operating in the 65-74 GHz range were utilized to create 18 different tag IDs. Each tag was measured ten times, creating a dataset of 180 measurements to train a classifier. To increase the amount of training data, the concept of data augmentation is utilized to generate more measurements derived from the original data by adding synthetic Additive White Gaussian Noise (AWGN) noise. This is achieved by computing the inverse FFT of the original EM signatures, followed by adding AWGN while maintaining a signal-to-noise ratio (SNR) of 45–54 dB. Finally, the FFT of these signals is computed to result in 200 measurements for each tag (200 × 18 = 3600 measurements). A 100% accuracy was achieved utilizing a neural network model with two hidden layers, rectified linear unit (ReLU) activation function, dropout regularization, and SoftMax loss.

Furthermore, in [20], two IDs encoded within the 4-6 GHz range are developed using circular patches. A DL-based long short-term memory network (LSTM) is utilized to achieve an accuracy of 93% when classifying between a cloned tag and an original one. For sensing applications, in [21], authors utilize ring resonators for temperature sensing over a range of 20°C to 100°C. The sensing was achieved by utilizing the properties of the oil, which is expected to change its permittivity values with an increase or decrease in temperature. The change in permittivity was then correlated with its effect on the resonant structures and their frequency responses. A dataset of 1209 EM samples was utilized to train the ML models. The Linear Regression (LR) and Random Forest (RF) ML models achieved a Root Mean Square Error (RMSE) of 4.40°C.

In our previous work [18], we used concentric rings in the 3.1-10.6 GHz range to create 255 different EM signatures (255 IDs), with each signature associated with six capacitive sensing states. Several ML models were trained on simulated EM responses of the tag. The RMSE of 1.32 for IDs and 0.032 pF for sensing was achieved using two different ML models, namely Support Vector Regression (SVR) and Gradient-Boosted trees (GBT), respectively.

Each study mentioned above achieved varying degrees of accuracy in the classification or prediction of continuous values, with some reaching near-perfect detection accuracy. These research efforts collectively demonstrate the effectiveness of ML and DL techniques in harnessing the intricate nature of CRFID EM signals for diverse applications.

IV. Discussion

Based on the literature published in this research area, some general trends can be observed. It was seen that all the papers utilized a supervised learning approach, where input-output pairs are provided to the model for learning. Table I reveals that an expensive VNA is a commonly used measurement instrument in several studies. The VNA plays a crucial role in characterizing and measuring the EM properties of CRFID tags in various frequency ranges. However, authors in [9] have utilized a custom modular reader, which is comparatively low-cost. Furthermore, in [20], VNA is replaced by a low-cost (<500 USD) walabot UWB reader for real-time processing. Another approach is given in [15], which utilizes low-cost ($2,000) Software Defined Radios (SDRs) to implement the reader showcasing a practical guide towards replacing expensive VNA. It was seen that the majority of the studies utilised measured data to train the ML models, with the exception of a few studies [14], [18], which evaluated the efficacy of the ML models with simulated data. The dataset size, which is a vital parameter when training ML/DL models, seems to vary from as little as 200 EM signals to 6,400 EM signals. The literature showed a sufficient amount of training, validation, and test data is required to validate the ML/DL model. Also, a trend of utilizing a two-antenna bi-static measurement setup is observed in the literature for enhanced isolation of transmit and receive paths. Based on the year of publication, it appears that there has been a noticeable increase in research activity in this field in recent years, especially from 2021 onwards. The trend seems to be increasing, with a significant number of papers published in 2023.

V. Challenges and Future Directions

While the integration of ML/DL and CRFID holds great promise, it also presents challenges and areas for further research and development. First, the quality and reliability of CRFID data used in the literature stand as paramount concerns. Ensuring data consistency and integrity is essential to facilitate the development of accurate ML/DL models. Furthermore, as seen in the literature, the data collection methodologies are either not mentioned or have been collected manually (i.e. placing the tag in front of the reader manually). An efficient and robust data collection methodology is necessary to ensure efficient and repeatable data collection. Effective solutions for data storage, processing, and analysis are essential to maintain consistency and repeatability of experiments. In our recent work, we proposed a robot-based automatic data acquisition methodology, which could be one of the solutions to ensure repeatability with large-scale and efficient data collection [24]. The trade-off between data sharing and safeguarding sensitive CRFID data is a matter of utmost importance, demanding robust data privacy and security measures to prevent unauthorized access and breaches [25]. In addition, many CRFID applications necessitate real-time data processing and decision-making, creating a crucial challenge for developers. In terms of scalability, ensuring that ML/DL models can accommodate the growing demands of the system without performance degradation is essential. Furthermore, given that CRFID tags are often constrained by limited power resources optimizing ML/DL algorithms to minimize power consumption emerges as a key consideration to develop robust CRFID systems.

TABLE I
COMPARISON OF THE STATE-OF-THE-ART OF ML METHODS IN CRFID[1]

Ref.	O.P/Fr. (GHz)	Tag Type	O/p Labels	Dataset/ Size	Reader	ML/DL Models	Accuracy/ Error
[9]	RCS/ 57-64	Alphanumeric characters	2 IDs	Measured/ -	BM/Custom	Fine Gaussian SVM, Subspace kNN Ensemble, Bagged Trees Ensemble, Weighted kNN, Fine kNN	≈ 96% (Subspace kNN Ensemble)
[10]	RCS/ 2-6	Concentric Rings	2 Plastic Types (IDs)	Measured EM signatures/ 200	BM/VNA	RF	90% (HB), 60-75% (NHB)
[11]	RCS/ 3-5.5	Split Ring Resonators	8	Measured/ -	BM/VNA	ANN	100%
[12]	Retr./ 1-10	Stub Resonators	2 IDs	Measured/ 816	BM/VNA	SVM	94.4%
[13]	RCS/ 65-74	C-shape overlapped to form E	18	Measured/ 3600	BM/PNA	ANN	100%
[14]	RCS/ 1-12	28 (Arabic Letters)	28	CST Simulated / 2184	BS/ -	BiLSTM	89%
[15]	RCS/ 2-3.5	Concentric Rings	4 IDs	Measured/ 1,140	BM/USRP N210 SDR	LR, SVM, RF, ANN, kNN	99.6%
[16]	RCS/ 1.5-5	Concentric Rings	16 IDs	Measured/ 2,400, and 6,400	MM/VNA	PCA+ Logistic Regression + probability study for soft classification	95 -100%
[17]	Retr./ 2.2-3.2	SIW	16 IDs	-	BM/VNA	Quantile Regression	-
[18]	RCS/ 3.1-10.6	Concentric Rings	1530 (255 IDs * 6 Capacitive Sensing States)	CST Simulated/ 1,530	MS/ -	SVR, DT, RF, GBT	RMSE: 1.32 (ID), 0.032 pF (Sensing)
[19]	Image/ 57-64	Alphanumeric characters	12 IDs	Measured/ 81	MM/VNA	CNN	-
[20]	RCS/ 4-6	Circular Patches	2	Measured/ -	- /Walabot	LSTM	93%
[21]	RCS/ 0-8	Ring Resonators	Temp. Sensing 20°C - 100°C	Measured/ 1,209	MM/VNA	LR, RF	RMSE 4.40°C%

[1]**Retr.** = Retransmission, **RCS** = Radar Cross Section, **O.P** = Operating Principle, **Fr.** Operating Frequency, **O/P** = Output, **MM** = Monostatic (Single Antenna Measurement), **BM** = BiStatic (Two Antenna Measurement), **-** = Information not available, **MS** = Monostatic Simulations, **BS** = BiStatic Simulations, **SIW** = Substrate Impedance Waveguide, **kNN** = k-Nearest Neighbors, **RF** = Random Forest, **ANN** = Artificial Neural Network, **SVM** = Support Vector Machine, **PCA** = Principal Component Analysis, **SVR** = Support Vector Regression, **GBT** = Gradient Boosting Trees, **DT** = Decision Tree, **LR** = Linear Regression, **LSTM** = Long Short-Term Memory, **N/HB** = Non/Homogenoeus Plastic Bales.

CRFID systems operate in noisy environments characterized by potential interference and reflections, adding complexity to data processing. Developing robust ML/DL models capable of effectively handling interference, varying surface shapes, orientations, read ranges, and noise is indispensable for maintaining reliability and accuracy. One of the solutions is to develop ML/DL models which incorporate these variations in the training data, as shown in our previous works in [26], [27]. Our findings demonstrate that ML/DL models accurately predict ID and sensing information. The models do so even in the presence of variations in tag bend scenarios when encountering different surface shapes or orientations. This showcases a robust detection technique.

However, a critical analysis of the SNR is currently missing in the literature, which is vital to evaluate the performance of ML/DL models along with portable, low-cost reader solutions to avoid wrong ID or sensing value detection. The performance metrics, such as speed of prediction and maximum read ranges, need to be studied for robust and reliable ML detection in CRFID systems for practical applications. Additionally, achieving model interpretability in complex algorithms is crucial, especially in applications like health monitoring, supply chain management and security. Understanding and explaining the decisions made by ML/DL models is paramount in trusting and improving the system's performance. Ensuring that ML/DL decisions are transparent and interpretable remains a challenge. Another aspect is the data capacity, and it was seen in most of the analysed literature that the data capacity is limited to 16 IDs with measured training data and 1530 IDs with simulated datasets. This is due to the huge amount of data collection required for high-capacity tags. Although the ML/DL models are shown to have generalized well on given datasets and patterns, a study on high-capacity tags (such as, for example, a 32-bit or 4294967295 IDs capacity tag) needs to be evaluated. Moreover, in future, the integration of CRFID, ML, and advanced sensors, such as environmental or physiological sensors, can enhance CRFID systems for environmental monitoring and healthcare applications, to name a few. Exploring edge computing solutions for real-time data processing directly on CRFID readers can lead to reduced latency and lessen the dependence on centralized servers. Dedicated ML/DL models tailored for CRFID security, encompassing functions like anomaly detection, intrusion detection, and authentication, are essential for safeguarding these systems. Establishing interoperability standards would pave the way for the seamless integration of CRFID systems with diverse platforms, ensuring compatibility and fostering widespread adoption.

VI. Conclusion

This paper has presented a comprehensive review of the current state-of-the-art of ML techniques used in CRFID technology. The integration of ML into CRFID shows significant promise, especially with the proficiency of ML models, particularly deep learning networks, in decoding intricate CRFID EM responses for precise identification and sensing. Current research trends indicate a growing interest in this field. Challenges such as data consistency, scalability, and real-time processing remain a challenge to address, along with power consumption optimizations. The future envisions deeper integration of CRFID, ML, and advanced sensors, particularly in fields like environmental monitoring and healthcare applications, with key areas of focus, including edge computing and the establishment of standardized interoperability. In summary, the synergy between CRFID and ML promises to be a significant area for future research to enhance the reliability of CRFID systems for real-world scenarios. With continued exploration of this intersection, we anticipate further innovations in chipless wireless identification and sensing technology.

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