Evaluation of a U-Shaped Convolutional Neural Network for RCS based Chipless RFID Systems

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***Abstract*—In this paper, for the first time, a one-dimensional convolutional neural network using a U-shaped architecture is evaluated in the context of radar cross section (RCS) based chipless RFID (CRFID) systems. A 3-bit CRFID tag is utilised to create eight discernible RCS signatures representing identification numbers. A dataset of 9,600 measured RCS signatures was utilised for training, validating, and testing the model. The dataset was collected by placing the tag on varying surface shapes, orientations, and read ranges to enable robust detection. The root mean square error (RMSE) metric was used to assess the model's performance. The achieved RMSE was 0.11 (1.5%). The low RMSE score demonstrates the effectiveness that this type of architecture has in accurately detecting and generalizing the encoded information from the RCS signatures.**

***Index Terms*—Chipless RFID, Convolutional Neural Networks, Electromagnetics, Radar Cross Section, Deep Learning, RFID, Robots.**

I. Introduction

The reflective pattern of an RCS-based Chipless RFID (CRFID) tag can be modified and thus used for encoding data by varying the tag antenna's shape, size, or material properties. The encoded data thus can only be retrieved from the scattered fields that reach back to the reader. There are, however, several dynamic interferences that take place while reading a tag which can not be avoided. Thus, efficient signal processing models must be developed to provide robustness in reading the scattered signals back from these tags. One of the ways explored in the literature is to use the pattern classification capabilities of Machine Learning (ML) to classify between different signatures and thus detect the correct tag information [1]–[3]. These studies have achieved impressive results in classifying CRFID tags based on their electromagnetic (EM) signatures and RCS characteristics. However, notable gaps in the existing literature need to be addressed. Specifically, the impact of varying surface shapes on CRFID tag detection has not been extensively investigated, despite its relevance to real-world applications. Additionally, the focus on classification tasks leaves a gap in the exploration of regression-based approaches for precise and continuous prediction of tag IDs. This study proposes a novel approach using a regression model based on a one-dimensional U-shaped Convolutional Neural Network (1D U-shaped CNN) for CRFID tag detection, which has not been previously explored in the literature. The 1D U-shaped CNN possesses an inherent advantage over other neural network architectures as it excels in capturing and leveraging sequential patterns, aligning with the one-dimensional nature of CRFID data [4]. The proposed model is designed to predict eight tag IDs and employs regression to predict tag IDs between 0 and 7. The work aims to enhance the accuracy and robustness of CRFID tag detection systems for broader Internet of Things (IoT) applications.

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II. Research Methodology

A. Tag Design and Data Encoding

This study utilised a flexible 3-bit polarization insensitive capacitive sensing RCS-based CRFID tag based on the design methodology discussed in [5]. The tag is developed using nested ring resonators for 3-bit data encoding. The information from the tag is retrieved by observing its RCS. As introduced in [5], the presence of the ring and its associated trough is utilised to represent bit '1', and their absence is used to represent bit '0'. In this study, each tag ID is associated with three sensing points related to the capacitance values of 0.1, 0.3 and 0.8 pF. The models can thus adapt to the changing sensing values, enhancing their ability to accurately detect tag IDs under varying conditions [6].

B. Data Collection and Machine Learning Implementation

For this study, 9,600 RCS EM signatures from the CRFID tag were acquired. We had a total of three tag variations for each ID, leading to a total of 24 characterised tags. The data was collected using an automated data acquisition methodology using the ur16e robot, discussed in [6]. The data was collected by placing the tag on five varying surface shapes, namely, Planar (Case I), Corner Bend-1 (Case II), Corner Bend-2 (Case III), cylindrical Bend-1 (Case IV), and cylindrical Bend-2 (Case V). For each case, the data was collected from two read range positions and a 45-degree tilt position (P_1,P_2,P_3,P_4), where P_1 and P_3 correspond to the two read ranges (200 and 300 mm), while P_2 and P_4 correspond to the 45-degree tilt at these two read ranges, respectively [6]. The collected data underwent a series of pre-processing steps to prepare it for adoption by the deep learning model. The raw RCS signatures were filtered using a fourth-order Butterworth filter with a cutoff frequency of 0.1 Hz. The parameters were selected based on a comprehensive analysis to effectively smoothen the signatures and reduce unwanted noise while retaining important features.

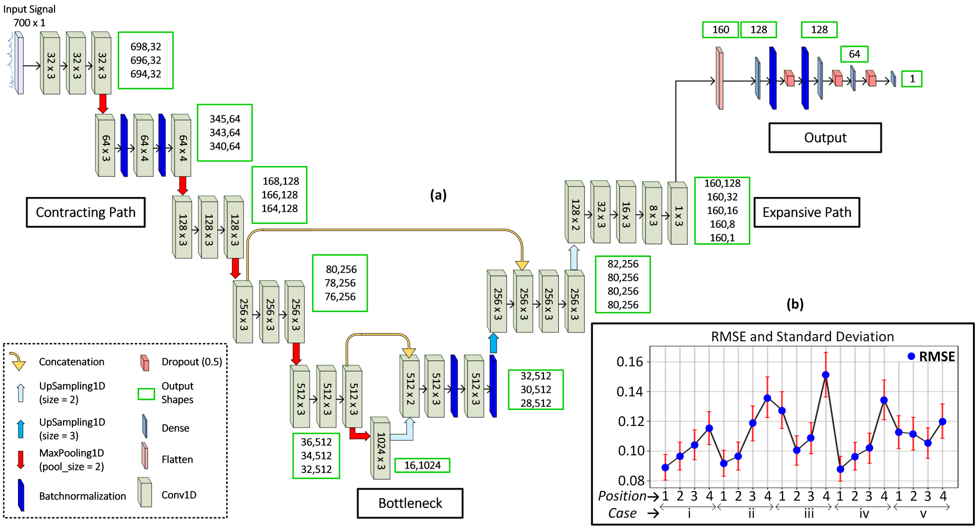

Fig. 1. (a) U-Net model architecture for one-dimensional regression on sequential data, (b) Summary of RMSE and standard deviation results for each case.

Further, the dataset was divided into training, validation, and test sets using a stratified split to maintain balanced label distribution. A 20% of the data was allocated to the test set for evaluation. The remaining 80% was divided into training and validation sets with a 75:25 split ratio, respectively. This division ensured a sufficient volume of data for training the model and effectively validating its performance. A standardization method, specifically the 'StandardScaler' from the scikit-learn library, was then applied to the training dataset. The mean and standard deviation obtained from the training set is then used to transform the validation and test sets. As shown in Fig.1(a), the proposed U-shaped architecture consists of a contracting and an expansive path. The input shape of the signal is (700, 1), representing the length of the input signal. The contracting path includes multiple convolutional layers with increasing filter sizes, followed by max-pooling layers for dimensionality reduction. The expansive path utilizes upsampling and concatenation operations to partially reconstruct the signal. Finally, data is flattened and inputted into a fully connected network. The model is compiled using the mean squared error (MSE) loss function and Adam optimizer. A Rectified Linear Unit (ReLU) activation function was utilized for all the convolutional layers. The model was trained for 300 epochs with a batch size of 32. To improve the process, an EarlyStopping callback was employed to monitor the loss and stop the training if no improvement occurred after 300 epochs. A ModelCheckpoint callback was utilised to save the best-performing model's weights, enabling easy resumption from the optimal weights. After training, predictions are made on the validation set and, if no overfitting is detected, the defined architecture is set and trained on the combined training and validation sets and evaluated on the test data, and the root mean squared error (RMSE) is calculated.

III. Results and Conclusion

The optimised U-shaped model achieved the RMSE of 0.12, 0.16, and 0.11 on the training, validation and test sets, respectively. The results show that the model generalised well on the unseen data with a low re-normalised RMSE of 1.5%. Furthermore, the RMSE for each individual case was evaluated for the given architecture. As seen in Fig.1(b), the results show the RMSE is slightly higher when the tag is placed in the longer read range scenario with a tilt of 45-degrees.

It can also be observed that the highest RMSE is observed for case III, which relates to the severe bent tag case. However, overall results are quite consistent, with RMSE included between 0.09 and 0.15 (e.g., $<2\%$ normalized RMSE) across the different cases. Moreover, the results demonstrate promising outcomes in the development of a robust model for detecting ID from surfaces with varying shapes. Also, by incorporating varying read range positions, along with a 45-degree tilt, the study simulates real-world scenarios with varying CRFID tag distances and angles. The model's successful detection and identification of tag ID under these diverse conditions demonstrate its adaptability and reliability.

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