

Article

Deep-Autoencoder-Based Radar Source Recognition: Addressing Large-Scale Imbalanced Data and Edge Computing Constraints

Yuehua Liu ^{1,2,†} , Xiaoyu Li ^{1,2,*,†}  and Jifei Fang ^{1,2}¹ Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100190, China; liuyh38@mail2.sysu.edu.cn (Y.L.); fangjf@aircas.ac.cn (J.F.)² Key Laboratory of Network Information System Technology, Institute of Electronics, Chinese Academy of Sciences, Beijing 100190, China

* Correspondence: lixy01@aircas.ac.cn

† These authors contributed equally to this work.

Abstract: Radar radiation source recognition technology is vital in electronic countermeasures, electromagnetic control, and air traffic management. Its primary function is to identify radar signals in real time by computing and inferring the parameters of intercepted signals. With the rapid advancement of AI technology, deep learning algorithms have shown promising results in addressing the challenges of radar radiation source recognition. However, significant obstacles remain: the radar radiation source data often exhibit large-scale, unbalanced sample distribution and incomplete sample labeling, resulting in limited training data resources. Additionally, in practical applications, models must be deployed on outdoor edge computing terminals, where the storage and computing capabilities of lightweight embedded systems are limited. This paper focuses on overcoming the constraints posed by data resources and edge computing capabilities to design and deploy large-scale radar radiation source recognition algorithms. Initially, it addresses the issues related to large-scale radar radiation source samples through data analysis, preprocessing, and feature selection, extracting and forming prior knowledge information. Subsequently, a model named RIR-DA (Radar ID Recognition based on Deep Learning Autoencoder) is developed, integrating this prior knowledge. The RIR-DA model successfully identified 96 radar radiation source targets with an accuracy exceeding 95% in a dataset characterized by a highly imbalanced sample distribution. To tackle the challenges of poor migration effects and low computational efficiency on lightweight edge computing platforms, a parallel acceleration scheme based on the embedded microprocessor T4240 is designed. This approach achieved a nearly eightfold increase in computational speed while maintaining the original training performance. Furthermore, an integrated solution for a radar radiation source intelligent detection system combining PC devices and edge devices is preliminarily designed. Experimental results demonstrate that, compared to existing radar radiation source target recognition algorithms, the proposed method offers superior model performance and greater practical extensibility. This research provides an innovative exploratory solution for the industrial application of deep learning models in radar radiation source recognition.

Keywords: radar target identification; deep autoencoders; imbalanced dataset; DNN hardware adaptation; edge artificial intelligence



Citation: Liu, Y.; Li, X.; Fang, J. Deep-Autoencoder-Based Radar Source Recognition: Addressing Large-Scale Imbalanced Data and Edge Computing Constraints. *Electronics* **2024**, *13*, 2891. <https://doi.org/10.3390/electronics13152891>

Academic Editor: Toshifumi Moriyma

Received: 30 June 2024

Revised: 19 July 2024

Accepted: 19 July 2024

Published: 23 July 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In the era of information warfare, non-contact electronic reconnaissance plays a pivotal role. Common electronic reconnaissance methods efficiently acquire the relevant electromagnetic parameters of enemy radar platforms and radar radiation sources. These parameters facilitate the subsequent analysis, identification, and localization of local radars and their platforms [1,2]. With the advancements in information processing and radar technologies, radars have embraced diverse and dynamic waveform designs to augment

performance and anti-interference capabilities [3]. As a result, there is a significant degree of overlap between radiation sources in the same frequency band and time, and the range of spectrum overlap is widening, thereby generating a complex electronic warfare environment. While we have made tremendous progress in AI, some limitations prevent many approaches from reaching industrial applications [4]. Firstly, the frequent updates and limited availability of large-scale radar radiation source signal databases, along with the prior knowledge of radar signals, pose challenges to the effectiveness and accuracy of radar radiation source identification models, especially in the context of emerging radar systems such as active phased arrays, frequency agility, multi-functionality, and three-dimensional coordinates [5]. Addressing the limitations of training data resources encountered in large-scale radar radiation source identification, how to effectively extract relevant prior knowledge from a vast array of complex radar reconnaissance signal data and establish high-performance deep neural network models has become a prominent research hotspot [6]. Secondly, since tasks such as radar signal reconnaissance and identification typically need to be conducted in complex environments like the outdoors, there is a practical scenario requirement for radar radiation source identification that necessitates the design of deep neural networks capable of operating on edge computing devices with inference speed and prediction accuracy that meet the required standards. However, edge computing devices that only integrate microprocessors have limitations in computational resources and storage space, leading to hardware resource constraints for deep-neural-network-based models. Therefore, how to design neural network models that are adapted to edge computing devices, enabling them to operate on smaller devices, reduce energy consumption, and collaborate with PC terminals for task processing through the network, is also an important research direction. In summary, in the practical application scenarios of large-scale radar radiation source identification, there is an urgent need to address the issues of unbalanced training data and insufficient storage and computing capabilities of lightweight edge computing devices. Therefore, a comprehensive solution that takes into account the limitations of data and computational resources is required to meet the demands of actual industrial applications.

To address the aforementioned issues, this paper proposes a model called RIR-DA, which is based on feature selection and deep autoencoders. The feature selection method is incorporated [7], which performs One-hot encoding for discrete feature values and batch normalization for continuous feature values. By leveraging the characteristics of feature information and utilizing the hierarchical adaptive learning of deep autoencoders, which promise results in classification tasks involving imbalanced samples, we enhance the model's capability for feature extraction through techniques such as reconstruction error analysis. The output stage employs the softmax function and its cross-entropy loss function. We also implement real-time adaptive adjustments to the learning rate based on variations in the validation loss, while ensuring effective convergence of the loss function through the use of the Adam optimization method. These measures collectively improve the performance of output classification. Synchronously, we introduce a parallel acceleration strategy for the RIR-DA model, developed using the NXP T4240 microprocessor. This strategy aims to transcend the storage and computational constraints typically associated with conventional edge hardware, offering an innovative solution for the effective deployment of deep learning models in edge computing environments. Through hardware-level optimizations and accelerations, the model's operational efficiency is significantly improved while maintaining its robustness and accuracy in complex settings, thereby reinforcing the technological foundation for edge computing applications in radar signal identification. Compared to the proposed methods, our research focuses on the practical requirements of industrial scenarios for large-scale radar radiation source identification. This paper offers a novel solution to mitigate the imbalance of sample data resources and the insufficiency of edge computing hardware resources, achieving commendable performance outcomes.

2. Related Work

2.1. Radar Radiation Identification Models

In the research of radar radiation source identification models, radar radiation source identification methods based on prior knowledge can be broadly classified into two main approaches: traditional machine learning methods [8] and deep learning methods [9]. In the traditional machine learning approach, the primary procedure for identifying radar radiation source targets involves manual feature engineering at the data level. The engineered features are subsequently employed for inference to obtain higher-level features. Finally, the acquired features are directly inputted into a classifier for training. The optimization based on Singular Value Decomposition was proposed in reference [10]. It introduces a feature extraction algorithm that utilizes weighted normalized Singular Value Decomposition. The features obtained from this algorithm can be inputted into various machine learning classification models for training. Common machine learning classification algorithms are widely applied to tasks involving the identification of radar radiation source targets. For example, support vector machines, random forests, the naive Bayes algorithm, and logistic regression can all be utilized for the recognition and classification of radar radiation sources [8]. However, traditional machine-learning-based methods for radar radiation source identification have two significant limitations. Firstly, the manual design and derivation of features is a cumbersome process that hinders the exploration of intrinsic relationships between features at a deeper level. Secondly, these methods are not suitable for large-scale radar radiation source target identification tasks. Compared to traditional machine learning methods, deep learning methods are better suited for large-scale radar radiation source target identification tasks [11–13]. Mainly, researchers in the field have utilized convolution neural networks (CNNs) to automatically extract higher-order features and feature combinations from radar radiation source data [14,15]. They have proposed a radar radiation source identification method based on feature transformation and CNNs, effectively addressing the identification of radar radiation source targets on a larger scale. However, practical application scenarios often involve sample issues such as incomplete sample labels and imbalanced data class distributions in individual radiation source recognition, which can lead to a decrease in classification accuracy. Deep autoencoders possess the capability to adaptively learn hierarchical feature representations and acquire more expressive higher-order features through the encoding–decoding process. A sea-surface target detection algorithm based on a stacked autoencoder (SAE) has been proposed, which has already been applied in the authors' coastal defense radar system [16]. Researchers have proposed a radar target recognition algorithm based on the decoupled representation variational autoencoder [17]. This method optimizes the network model parameters by separately modeling inter-class characteristic representations and inter-class common representations, thereby achieving effective feature extraction for high-resolution radar distance data with high separability. For better performance, a model based on generative adversarial networks (GANs) with a Gramian angular field has been proposed in the literature to tackle the classification of specific radiation sources [18]. Analogously, a method based on the Synthetic Minority Oversampling Technique (SMOTE) is presented to generate a larger number of minority samples in the database for identifying radar radiation sources with category imbalance [19]. Nevertheless, when dealing with large-scale imbalanced samples of radar radiation sources, certain technical challenges still exist, necessitating the adoption of new technical models to address the problem of target identification under such conditions.

2.2. Neural Network on Edge Devices

In the research on model deployment and inference on edge computing devices, the mainstream direction is to achieve low latency, high reliability, and bandwidth optimization for intelligent identification algorithms of large-scale radar radiation sources, under the constraints of limited computational and storage resources. Although deep neural networks possess high-performance recognition capabilities, their complex architecture

and extensive parameterization also place higher demands on the storage and computational resources of edge computing devices equipped with integrated microprocessors [20]. Therefore, the deployment and inference of these networks largely rely on the enhancement of two aspects of capabilities. On one hand, edge computing devices must provide sufficient computational power and support for parallel processing and ensure high data throughput. On the other hand, and more importantly, they rely on the design of adaptive parallel acceleration methods for neural networks in conjunction with the characteristics of the hardware platform. Overall, the field of artificial intelligence hardware acceleration is currently undergoing a key transition from alleviating bandwidth limitations to improving computational performance. Leading semiconductor companies, including NVIDIA, Intel, and AMD, have introduced specialized AI hardware platforms, each meticulously crafted to meet the computational requirements of deep learning models [21,22]. The T4240 multi-core communication processor from NXP Semiconductors, a flagship product in the QorIQ® T series, integrates hardware acceleration tailored for machine learning models, advanced networking services, and an expansive suite of system peripheral expansion interfaces. These features have established the T4240 as a popular selection for diverse industrial applications, especially those that require high-performance computation and rapid response capabilities [23]. In addressing the integration requirements for microprocessors, researchers have proposed an efficient FPGA implementation of convolutional neural networks for radar emitter signal recognition [24], as well as a design approach for high-performance Fast Fourier Transform FPGA processors for radar signal processing [25]. With the evolution of GPU parallel computing, researchers have also suggested considering the limitations of CPU computational capabilities when designing large-scale software-defined radar systems, proposing a feasible solution that utilizes GPU parallel acceleration for signal processing [26]. The aforementioned methods offer valuable guidance for the deployment of radar radiation source identification algorithms on cloud-based GPU devices and terminal FPGA devices. However, when focusing on scenarios that require lightweight network adaptation for hardware acceleration on smaller microprocessors, there is still a deficiency in theoretical analysis and computational methods for hardware acceleration on adaptive edge computing platforms.

3. Empirical Feature Selection

3.1. Dataset

The data used in this study were derived from radar signal simulation data. In the simulation experiment, the signal-to-noise ratio (SNR) ranged from 10 to 20 dB, with a step size of 2 dB, and the noise was additive white Gaussian. The acquired dataset contains a total of 1,662,445 radar emission samples, covering 96 different radar models. While the dataset contained hundreds of potentially discriminative signal features, due to similarities in the modulation patterns of some features, the analysis involved outlier processing and feature comparison. Consequently, this work discarded the similar and irrelevant features, retaining 12 high-value signal features. Of these twelve features, three are discrete-valued, and nine are continuous-valued.

The types of features include carrier frequency, pulse width, and pulse repetition interval. Carrier frequency refers to the frequency of the high-power electromagnetic wave signal generated by the radar transmitter prior to modulation. Pulse width denotes the temporal duration of the pulse signal in a pulse-modulated radar. Pulse repetition interval signifies the time duration between two consecutive pulses.

The initial step involved partitioning the full dataset, which comprised 1,662,445 radar radiation source samples, into two subsets: a large dataset (with more than 1100 samples per rid class) and a small dataset (with fewer than 1,100 samples per rid class). The large dataset consisted of a total of 1,640,061 samples, whereas the small dataset contained 22,384 samples. Subsequently, separate analyses were conducted to examine the distribution of the 96 rid classes within the full dataset, large dataset, and small dataset. The statistical results are presented in Figure 1. The findings reveal a highly imbalanced sample distribution in real-

world scenarios, with both the large and small datasets exhibiting a long-tail distribution pattern. Specifically, certain classes demonstrate a substantial number of samples, while the majority of classes have a limited number of samples. This distribution pattern significantly amplifies the challenges associated with model recognition.

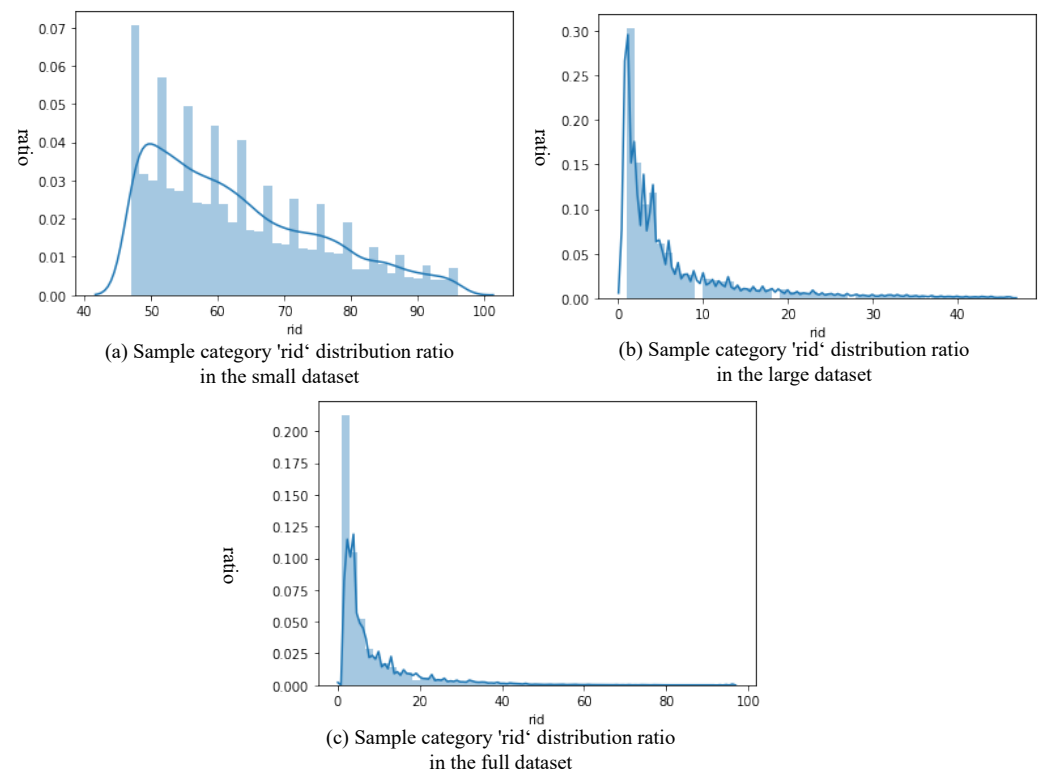


Figure 1. The distribution ratio of radar source target category rid in the different sample sets.

3.2. Feature Encoding Design

For discrete value features, we employ the One-hot encoding method for processing. Through One-hot encoding, the three discrete value features are transformed into 34 binary encoded features. Consequently, the feature vector of an individual sample expands from 12 dimensions to 43 dimensions, effectively replacing the original three discrete value features with the addition of 34 binary encoded parameters for feature representation. This approach offers two key advantages: Firstly, by enabling more precise parameter management, this approach enhances the non-linear capability of the classification model. This is crucial as it allows the model to better capture complex, non-linear relationships within the data, which is often essential for achieving high predictive performance. In addition, the approach reduces the impact of feature perturbation on the model's stability and mitigates the influence of noise. This enhancement of the model's robustness is particularly beneficial, as it makes the model less sensitive to minor variations or imperfections in the input data, thereby improving the reliability and consistency of its predictions.

3.3. Normalization for Continuous Feature Values

In order to mitigate the impact of large numerical ranges present in continuous feature values, we employed Z-score normalization. This normalization technique proportionally scales the features, thereby ensuring that the data distribution is confined within a specific range. Formula (1) for calculating the standard deviation and executing the Z-score normalization transformation is provided below:

$$\sigma = \sqrt{\frac{1}{n} \times \sum_{i=1}^n (x_i - \mu)^2},$$

$$z_i = \frac{x_i - \mu}{\sigma}$$
(1)

where n represents the total number of samples, μ denotes the relative mean, and σ represents the standard deviation. The purpose of this transformation is to eliminate the dimensions of the original data, x , ensuring the consistent scale of different features, which facilitates comparison and calculation.

4. RIR-DA Model

4.1. Deep Autoencoder Model

The deep autoencoder [15] comprises two symmetric deep neural networks. Generally, the first half corresponds to the encoding part of the network, while the second half corresponds to the decoding part. The network architecture of the deep autoencoder implemented in this study is depicted in Figure 2.

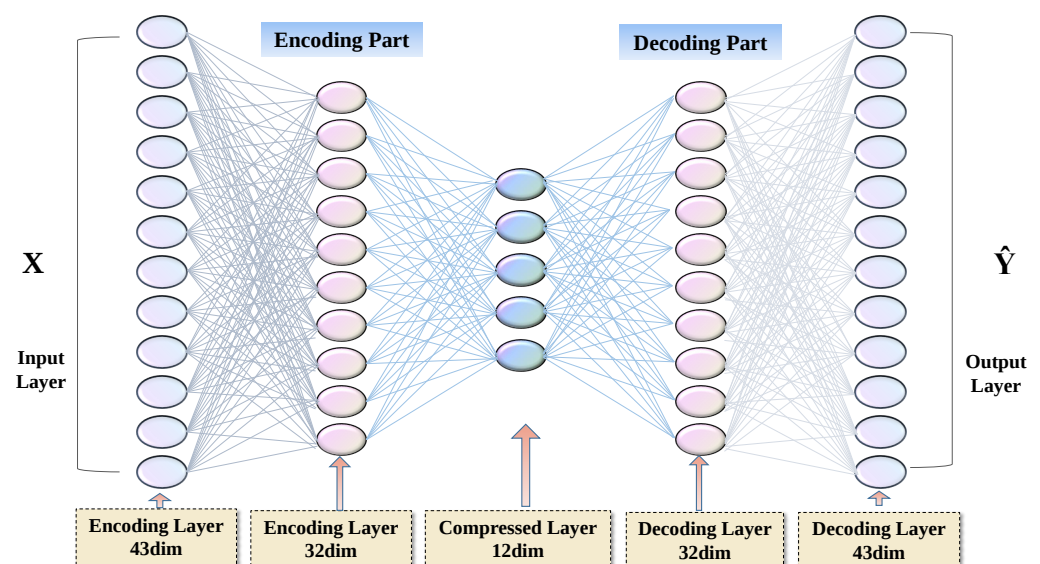


Figure 2. The RIR-DA model framework.

By means of the encoding–decoding process, an autoencoder effectively utilizes data features for self-reconstruction. In recognition tasks characterized by highly imbalanced samples, the reconstruction error of a minority sample after autoencoding may exceed the errors of the majority of samples. Therefore, as indicated in (2), the algorithm utilizes an improved regularized loss function [27]:

$$F(x, \hat{x}) = \mathcal{L}(x, \hat{x}) + \lambda \|J_f(x)\|_F$$

$$= \mathcal{L}(x, \hat{x}) + \lambda \sum_i \left\| \nabla_x a_i^{(h)}(x) \right\|^2$$
(2)

where $\nabla_x a_i^{(h)}(x)$ refers to the gradient field of the hidden layer activations that is dependent on the input x . The regularization term on the right-hand side is composed of the Jacobian matrix J under the Frobenius norm, which penalizes the model's weight parameters to prevent overfitting. The calculation represented by (3), considering m input values and n hidden layer nodes, can be expressed as follows [27]:

$$\|J_{f(x)}\|_F = \begin{bmatrix} \frac{\delta a_1^{(h)}(x)}{\delta x_1} & \dots & \frac{\delta a_1^{(h)}(x)}{\delta x_m} \\ \vdots & \ddots & \vdots \\ \frac{\delta a_n^{(h)}(x)}{\delta x_1} & \dots & \frac{\delta a_n^{(h)}(x)}{\delta x_m} \end{bmatrix} \quad (3)$$

4.2. RIR-DA Model Architecture

The autoencoder effectively learns the distinguishing features between the minority class and majority samples by leveraging negative instances from the minority samples. Building upon this concept and considering the highly imbalanced distribution of the entire sample set, we propose RIR-DA, a deep-autoencoder-based model for the automatic identification of radar radiation sources. Figure 3 illustrates the network architecture of the RIR-DA model.

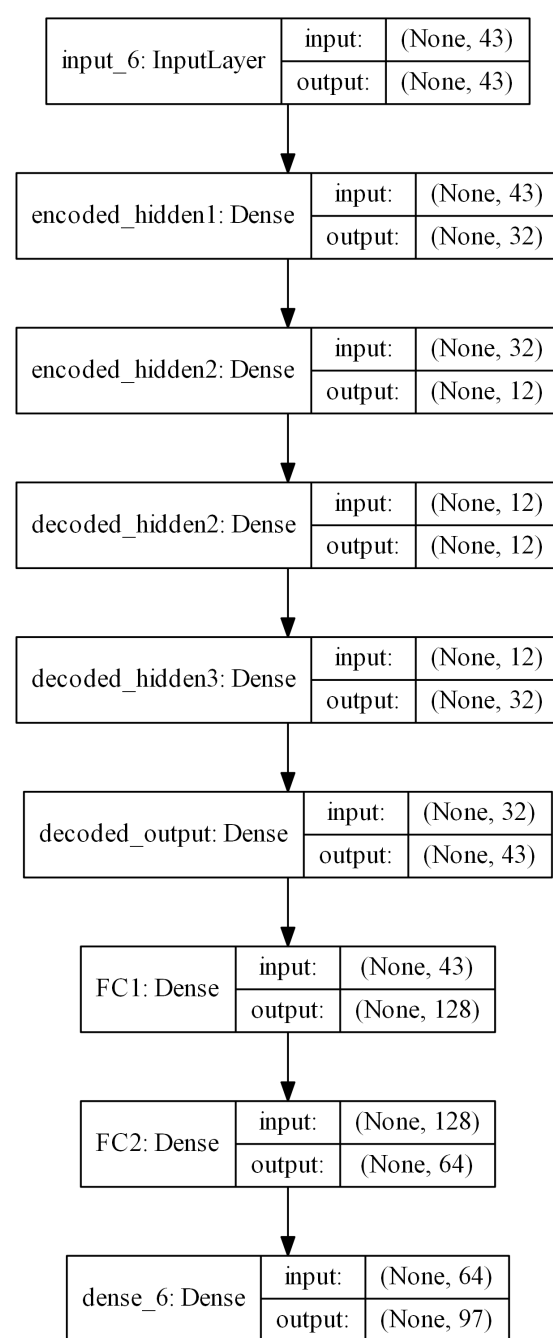


Figure 3. RIR-DA model network structure diagram.

In order to mitigate the challenges posed by the limited sample size in the small dataset, we have appropriately streamlined the complexity of the RIR-DA network structure, enabling it to better handle learning tasks with a limited number of samples.

4.3. Model Loss Function Optimization

The model employs the widely adopted cross-entropy loss function for classifying model outputs in multi-class classification tasks. Formula (4) for the cross-entropy loss function is as follows [28]:

$$loss = - \sum_{i=1}^n y_{i1}' \log y_{i1}' + y_{i2}' \log y_{i2}' + \dots + y_{im}' \log y_{im}' \quad (4)$$

where the number of classes is denoted as m and the number of samples as n . The derivative Formula (5) for the loss is given as follows:

$$\frac{\partial loss}{\partial y_{i1}} = - \sum_{i=1}^n \frac{y_{i1}'}{y_{i1}}, \dots, \frac{\partial loss}{\partial y_{im}} = - \sum_{i=1}^n \frac{y_{im}'}{y_{im}} \quad (5)$$

Regarding the derivative calculation for the softmax-cross-entropy loss, we apply the chain rule, which yields the following expression as shown in (6):

$$\frac{\partial loss}{\partial w_n} = \frac{\partial loss}{\partial y_j'} \times \frac{\partial y_j'}{\partial y_i} \times \frac{\partial y_i}{\partial w_n} = (y_i' - 1)w_n \quad (6)$$

In this study, we utilize the Adam algorithm to minimize the loss. Adam is an adaptive learning rate optimization algorithm that combines the RMSprop and Momentum optimization algorithms [29].

5. Model Hardware Acceleration Solution

5.1. NXP T4240 Microprocessor

The NXP T4240 microprocessor, belonging to the QorIQ® T series, is utilized for computational tasks within the deep neural network model. It serves as the flagship product of the series, featuring 12 dual-threaded e6500 cores, providing a total of 24 threads. Each core of the T4240 is equipped with an AltiVec engine that supports Single Instruction Multiple Data (SIMD) technology, enabling a peak computing rate of up to 193 GFLOPS. The cores are organized into clusters, with four cores forming one cluster. Each cluster shares a 2 MB level 2 cache, resulting in a total cache size of 6 MB. The processor operates at a maximum frequency of 1.8GHz and supports a 64-bit Instruction Set Architecture (ISA). It supports three levels of instructions: user, supervisor, and system management programs. Additionally, the T4240 offers a comprehensive range of I/O interfaces and network components, including two serial RAPIDIO interfaces, two serial ATA controllers, two USB controllers, four I2C controllers, three 8-channel DMA controllers, and 32-channel SerDES interfaces. It integrates 1 Gbps and 10 Gbps Ethernet, hardware acceleration, and advanced system peripherals. As a microprocessor, the T4240 provides powerful computational capabilities and abundant interfaces. Furthermore, it supports the real-time operating system VxWorks, making it suitable for deploying neural network models and other applications in intelligent terminals and devices.

5.2. Hardware Adaptation of RIR-DA Model Architecture

The RIR-DA model, illustrated in Figure 3, is specifically designed for the automatic identification of 96 individual radiation sources, with a maximum input signal length of 1024 dimensions. The model's initial layer encompasses preprocessing and normalization, which process and generate 43-dimensional raw features. The input to the first encoding layer consists of the 43-dimensional radiation source features, which undergo encoding to

yield 32-dimensional features. In the subsequent encoding layer, 12-dimensional advanced features are further extracted. The third decoding layer decodes the 12-dimensional advanced features back to 32 dimensions, followed by the fourth layer which decodes the 32-dimensional features back to the original 43-dimensional raw features. Subsequently, fully connected layers with dimensions of 128 and 64 are interconnected, and the final fully connected layer utilizes the softmax function as a non-linear activation function. The network output provides the probabilities for classifying the input radiation sources into 96 distinct categories.

The RIR-DA network architecture was implemented using TensorFlow for the actual encoding process. After completing the training phase, the RIR-DA autoencoder network was deployed on the NXP T4240 microprocessor to enable automatic identification of radiation sources. This was achieved by performing forward propagation calculations on the input radiation source signals. TensorFlow offers a comprehensive set of computational APIs for deep neural networks, encompassing encoding, decoding, and non-linear activation operations, which were utilized in the model's computations. Throughout the training process, the Adam algorithm was employed in TensorFlow to optimize the parameters, calculate gradients, and automatically update the network parameters during iterations.

Upon analyzing the aforementioned encoding and decoding processes, it is evident that the first encoding layer consists of 43 weight parameters and bias parameters. The second encoding layer comprises 32 weight parameters and bias parameters, while the third layer utilizes 12 weight parameters and bias parameters to obtain compressed features. In the fourth decoding layer, there are 32 weight parameters and bias parameters, and the fifth decoding layer contains 43 weight parameters and bias parameters. Consequently, the entire network consists of a total of 910 parameters. To ensure efficient implementation, the network employs 16-bit fixed-point arithmetic, resulting in a storage space requirement of no more than 1 MB.

Within the RIR-DA model, special consideration must be given to the implementation of the ReLU function, fully connected operations, and softmax function. The ReLU function can be achieved by utilizing VSIPL's value comparison functions, which encapsulate AltiVec technology and compare the input with zero. The softmax function can be implemented through exponential, multiplication, and division operations available in VSIPL. Therefore, the model can be seamlessly ported and executed on the T4240 microprocessor.

5.3. Evaluation of Hardware Acceleration Performance

Considering that the input data for each layer of the network are 16 bits, and the T4240 microprocessor is equipped with a 128-bit vector processor called AltiVec Vector Register, the processor can simultaneously load 8 input data values. By leveraging SIMD parallelism, it becomes possible to compute 8 outputs concurrently. This parallel acceleration solution describes the neural network algorithm as matrix operations and utilizes SIMD technology to expedite matrix computations. The encoding layer, decoding layer, fully connected layer, and output layer of the RIR-DA model can all be treated as parameter matrices. Notably, upon analysis, it is observed that the number of matrix multiplication and addition operations is divisible by 8, allowing for the implementation of SIMD vector operations. In summary, this solution leverages hardware and matrix parallel computation acceleration on the NXP T4240 microprocessor. With a peak processor frequency of 1.5 GHz, the average processing time for RIR-DA is 21.16 μ s, maintaining the performance achieved during training.

5.4. Intelligent Identification System

In the research field of radar signal recognition, the development of micro-embedded computing platforms has reached a new level, as their current computational capabilities can now meet the requirements of deep learning algorithms for complex classification and recognition tasks. This study proposes an innovative design scheme for an intelligent radar emitter recognition micro-system based on an edge computing device, with the NXP QorIQ

T4240 as the core processing unit. As shown in Figure 4, the system is carefully designed with two main modules: the computer-side module and the edge-computing-side module. The computer-side module is responsible for data collection, dataset construction, and deep learning model training based on the RIR-DA network. It establishes a TCP communication protocol to achieve efficient two-way data transmission and information exchange with the NXP QorIQ T4240 device. The edge-side module focuses on executing real-time signal acquisition, feature selection, normalization preprocessing, as well as the parallel execution and inference computation of the deep learning model. The radar emitter recognition results are then fed back to the computer-side module through TCP communication.

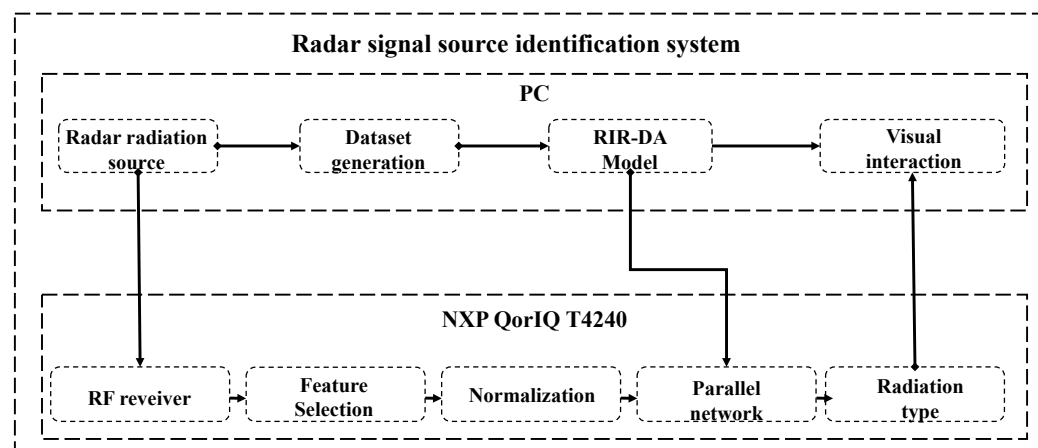


Figure 4. Radar radiation source signal intelligent identification system infrastructure.

During the initial system operation, thorough initialization is first carried out on the computer client and edge computing device. The pre-trained deep learning model is then loaded on the logged-in NXP QorIQ T4240, and the parallel hardware acceleration inference function is launched, while a stable TCP communication connection is established with the computer client. In this process, the edge side is able to directly receive the radar emitter signals and execute the inference and recognition tasks. Additionally, to enhance the model's generalization capability, the computer client can provide simulated signals, which are then transmitted in real time to the edge computing device for model inference and recognition. The edge computing device subsequently returns the inference results to the computer side. This use of simulated signals enables direct feedback on the model's performance, which allows for analysis and further optimization, if necessary.

Regarding system optimization, when the system identifies the need for model performance improvement, the computer side first accumulates a larger sample set of radiation source data. Once the sample size reaches a sufficient scale, incremental training of the base model is initiated. During the training process, simulated signals are used periodically to evaluate the model's recognition capability, in order to avoid overfitting. The training process is terminated when the model's recognition performance meets the engineering application requirements, and the updated model is then synchronized to the edge computing device. This edge-cloud collaborative online learning mechanism enables the system to continuously perform online learning on the externally collected radiation source signals, thereby constantly enhancing the system's recognition performance and adaptability. Adopting this approach not only improves the system's practicality and reliability but also provides a new and efficient solution for the radar signal recognition domain.

6. Experimental Results

The proportions of the training, validation, and testing sets were set at 7:1:2. During the training process, we incorporated a learning rate decay technique along with the Adam optimization algorithm for the RIR-DA model.

Consistent Convergence Behavior. The results presented in the Figure 5 demonstrate the strong training performance and robustness of the RIR-DA model. Across all three dataset sizes, the model exhibits rapid convergence of the training loss and validation loss, indicating it can efficiently learn the underlying patterns in the data regardless of the dataset size. Notably, the convergence patterns remain remarkably consistent, suggesting the RIR-DA model maintains its effectiveness in learning even as the dataset size is reduced. While the small dataset shows higher overall loss values, the consistent convergence behavior implies the model can leverage additional data to further improve its performance as the dataset size increases. This consistent convergence across varying dataset sizes underscores the RIR-DA model's robustness to changes in the amount of training data, a desirable property for practical applications where the model may need to be applied to imbalanced datasets.

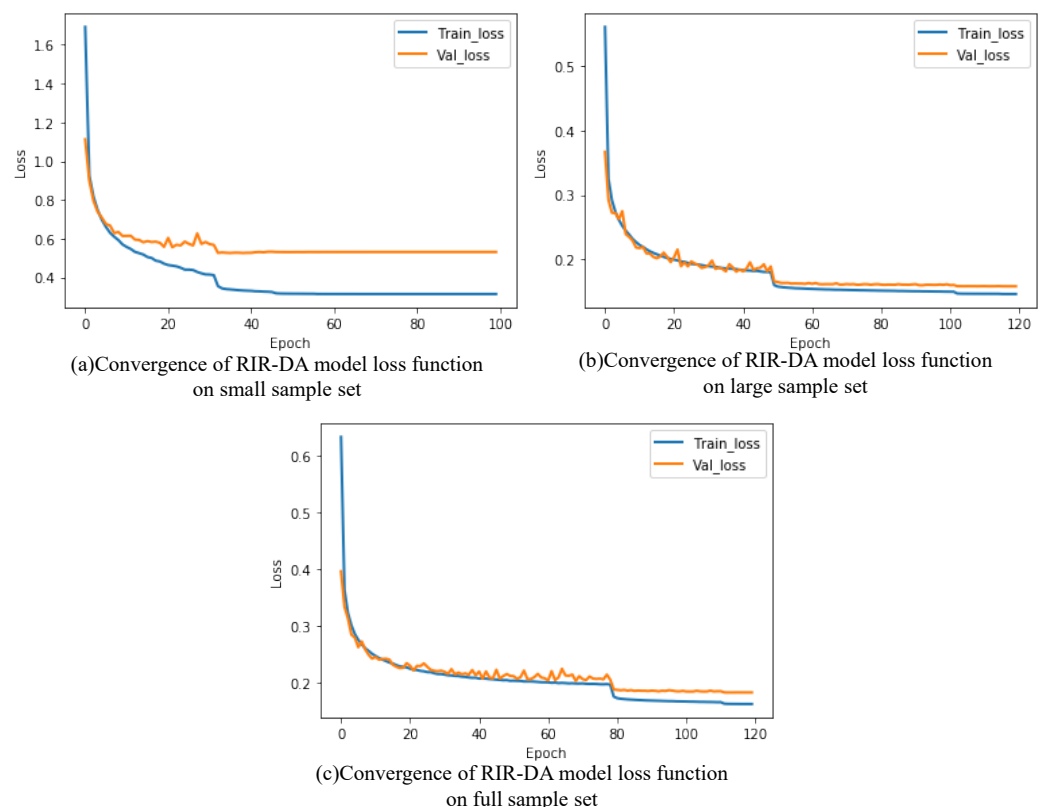


Figure 5. Convergence of RIR-DA model loss on different sample sets.

Approximate Categorical Accuracy. The results in the Figure 6 demonstrates the RIR-DA model's approximate performance and versatility across various dataset sizes. The model exhibits rapid convergence and high accuracy, excelling on large and full sample sets by achieving near-perfect accuracy and robust generalization. Despite some gaps between training and validation accuracy on smaller datasets, the model maintains high performance, indicating its effective handling of diverse data scenarios. These findings highlight the model's scalability and effectiveness, suggesting that it is effectively learning the patterns in the data and generalizing them well to new, unseen data.

Test in Line with Expectations. The RIR-DA model's exceptional performance across the various dataset sizes, as demonstrated in Table 1, is in line with expectations and a clear testament to its exceptional capabilities. The model is able to maintain high classification accuracies of 95.6%, 96.0%, and 83.9% on the full, large, and small sample datasets, respectively. This high accuracy level suggests the model has a strong grasp of the underlying patterns and complexities within the imbalanced dataset.

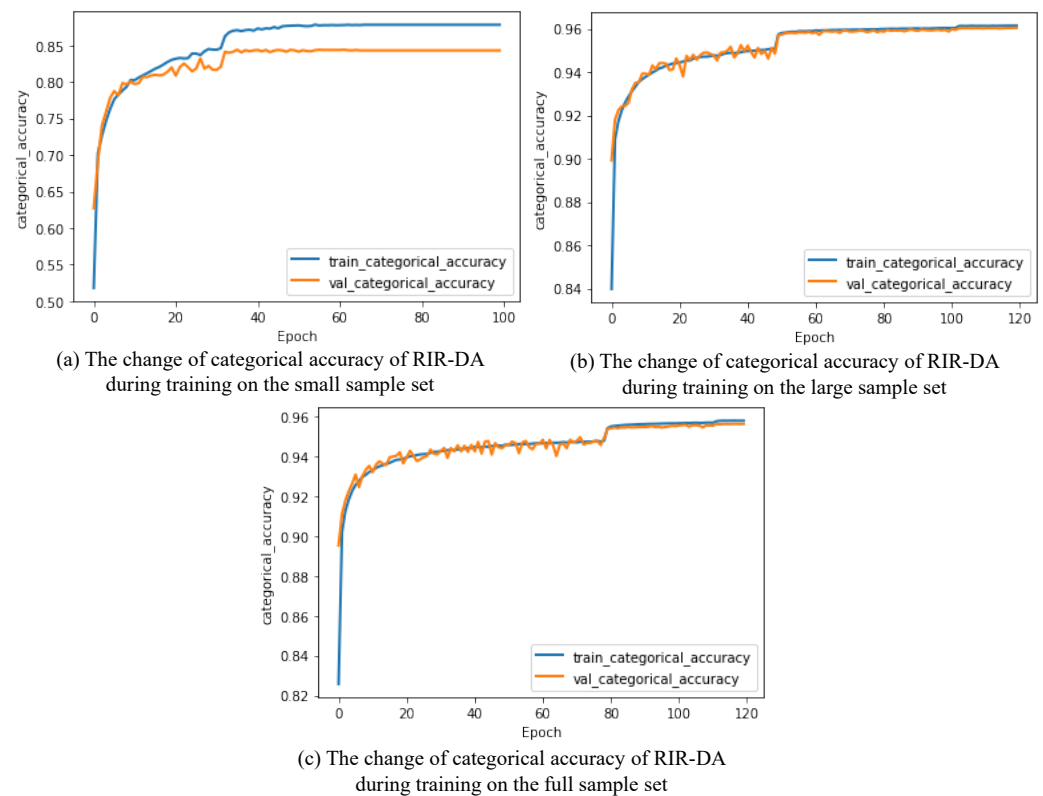


Figure 6. The change in categorical accuracy of RIR-DA during training on the different sample sets.

Table 1. The complete experimental results for different type of datasets.

Test Set Type	Sample Count	Time	Accuracy
Full Sample Dataset	249,367	5.29 s	95.6%
Large Sample Dataset	246,010	5.07 s	96.0%
Small Sample Dataset	3358	0.09 s	83.9%

Efficiency evaluation in large-scale samples. In comparison to previous research methods that achieved over 90% accuracy in radar radiation source identification, our RIR-DA model exhibits superior performance on a larger-scale radar radiation source dataset, as evidenced in Table 2. The experimental results validate the effectiveness of our proposed radar radiation source identification method, which incorporates feature selection and deep autoencoders. The method demonstrates promising initial results on a large-scale radar radiation source dataset that closely resembles real-world data.

Table 2. Processing capability comparison of previous models with the same level of accuracy performance.

Model	Accuracy (Full Sample)	Radar Signal Number	Dataset Volume
SVM	$\geq 90\%$	11	10^4
Adaboost	$\geq 93\%$	20	10^4
NN	$\geq 91\%$	20	10^4
U-CNN	$\geq 95\%$	67	10^5
RIR-DA	$\geq 95\%$	96	10^6

7. Conclusions

This paper introduces a novel approach to radar emitter identification in industrial applications, effectively mitigating constraints related to training data and edge computing resources. The RIR-DA model, utilizing deep autoencoders and prior knowledge, has

achieved over 95% accuracy in processing large-scale, imbalanced datasets, identifying 96 radar emitter targets. Leveraging the computational efficiency of the T4240 embedded microprocessor, this study proposes a model parallel acceleration scheme, resulting in nearly an eightfold enhancement in computational speed.

Future research should delve into data augmentation techniques to manage the scale and imbalance inherent in radar emitter datasets. Concurrently, research efforts should focus on developing model compression and acceleration algorithms to accommodate the storage and computational limitations of edge computing environments. Moreover, prioritizing model interpretability and security is essential for bolstering the model's stability and reliability in sophisticated electronic contexts.

The model parallel acceleration and integration strategies outlined in this study pave the way for innovative industrial applications of radar emitter identification technology. Integrating this technology deeply with modern information technologies like the Internet of Things, big data, and cloud computing may facilitate the creation of more intelligent and automated radar signal monitoring and analysis systems. Cross-disciplinary collaboration has the potential to expand the application of radar emitter identification technology into domains such as intelligent transportation, public safety, and environmental monitoring, thereby maximizing its value.

In summary, this study provides new perspectives and methods for developing radar emitter identification technology and explores its industrial application pathways. Ongoing technological advancements and innovation suggest that radar emitter identification technology will play a pivotal role across various sectors.

Author Contributions: Conceptualization, Y.L., X.L. and J.F.; methodology, Y.L., X.L. and J.F.; software, Y.L. and X.L.; validation, Y.L., X.L. and J.F.; formal analysis, Y.L. and X.L.; investigation, Y.L., X.L. and J.F.; resources, J.F.; data curation, J.F. and Y.L.; writing—original draft preparation, X.L.; writing—review and editing, X.L.; visualization, X.L.; supervision, X.L., Y.L. and J.F.; project administration, X.L. and Y.L.; funding acquisition, Y.L., X.L. and J.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by “Container Cloud Engine and Deployment Service” project under grant No. E3E31207.

Data Availability Statement: As the data of radar radiation source are used in this study, which involve privacy information, if researchers need to use it, please contact the author to obtain desensitization data.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

- Butt, F.A.; Jalil, M. An overview of electronic warfare in radar systems. In Proceedings of the 2013 The International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAECE), Konya, Turkey, 9–11 May 2013; pp. 213–217.
- Li, D.; Gu, L.; Zhu, L. Identification and parameter estimation algorithm of radar signal subtle features. *Phys. Commun.* **2020**, *42*, 101140. [[CrossRef](#)]
- Oyedare, T.; Shah, V.K.; Jakubisin, D.J.; Reed, J.H. Interference suppression using deep learning: Current approaches and open challenges. *IEEE Access* **2022**, *10*, 66238–66266. [[CrossRef](#)]
- Debauche, O.; Mahmoudi, S.; Mahmoudi, S.A.; Manneback, P.; Bindelle, J.; Lebeau, F. Edge computing and artificial intelligence for real-time poultry monitoring. *Procedia Comput. Sci.* **2020**, *175*, 534–541. [[CrossRef](#)]
- Binetti, M.S.; Campanale, C.; Massarelli, C.; Uricchio, V.F. The use of weather radar data: Possibilities, challenges and advanced applications. *Earth* **2022**, *3*, 157–171. [[CrossRef](#)]
- Jiang, W.; Wang, Y.; Li, Y.; Lin, Y.; Shen, W. Radar target characterization and deep learning in radar automatic target recognition: A review. *Remote Sens.* **2023**, *15*, 3742. [[CrossRef](#)]
- Quan, D.; Tang, Z.; Chen, Y.; Lou, W.; Wang, X.; Zhang, D. Radar emitter signal recognition based on MSST and HOG feature extraction. *J. Beijing Univ. Aeronaut. Astronaut.* **2022**, *49*, 538–547. [[CrossRef](#)]

8. Li, P. Research on radar signal recognition based on automatic machine learning. *Neural Comput. Appl.* **2020**, *32*, 1959–1969. [[CrossRef](#)]
9. Geng, Z.; Yan, H.; Zhang, J.; Zhu, D. Deep-learning for radar: A survey. *IEEE Access* **2021**, *9*, 141800–141818. [[CrossRef](#)]
10. Chen, K.; Zhang, S.; Zhu, L.; Chen, S.; Zhao, H. Modulation recognition of radar signals based on adaptive singular value reconstruction and deep residual learning. *Sensors* **2021**, *21*, 449. [[CrossRef](#)]
11. Pan, M.; Liu, A.; Yu, Y.; Wang, P.; Li, J.; Liu, Y.; Lv, S.; Zhu, H. Radar HRRP target recognition model based on a stacked CNN-Bi-RNN with attention mechanism. *IEEE Trans. Geosci. Remote Sens.* **2021**, *60*, 1–14. [[CrossRef](#)]
12. Liu, X.; Wang, L.; Bai, X. End-to-end radar HRRP target recognition based on integrated denoising and recognition network. *Remote Sens.* **2022**, *14*, 5254. [[CrossRef](#)]
13. Du, C.; Tian, L.; Chen, B.; Zhang, L.; Chen, W.; Liu, H. Region-factorized recurrent attentional network with deep clustering for radar HRRP target recognition. *Signal Process.* **2021**, *183*, 108010. [[CrossRef](#)]
14. Wang, X. Electronic radar signal recognition based on wavelet transform and convolution neural network. *Alex. Eng. J.* **2022**, *61*, 3559–3569. [[CrossRef](#)]
15. Lee, B.H.; Lee, S.; Kang, S.; Kim, S.C.; Kim, Y.H. Radar target classification considering unknown classes using deep convolutional neural network ensemble. *IET Radar, Sonar Navig.* **2021**, *15*, 1325–1339. [[CrossRef](#)]
16. Yan, H.; Chen, C.; Jin, G.; Zhang, J.; Zhang, G.; Zhu, D. Detection of sea-surface target of coastal defense radar based on Stacked Autoencoder (SAE) algorithm. *IET Radar Sonar Navig.* **2022**, *16*, 291–305. [[CrossRef](#)]
17. Liu, Q.; Zhang, X.; Liu, Y. A Prior-Knowledge-Guided Neural Network Based on Supervised Contrastive Learning for Radar HRRP Recognition. *IEEE Trans. Aerosp. Electron. Syst.* **2024**, *60*, 2854–2873. [[CrossRef](#)]
18. Zhang, Y.; Zhou, Z.; Li, X. Generative adversarial networks with Gramian angular field for handling imbalanced data in specific emitter identification. *Signal Image Video Process.* **2024**, *18*, 2929–2938. [[CrossRef](#)]
19. Ma, W. SMOTE-based Category Imbalance for Radar Radiation Source Sorting and Identification. In Proceedings of the 2020 IEEE International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), Chongqing, China, 6–8 November 2020; Volume 1, pp. 1291–1294. [[CrossRef](#)]
20. Li, E.; Zeng, L.; Zhou, Z.; Chen, X. Edge AI: On-demand accelerating deep neural network inference via edge computing. *IEEE Trans. Wirel. Commun.* **2019**, *19*, 447–457. [[CrossRef](#)]
21. Khan, F.H.; Pasha, M.A.; Masud, S. Advancements in microprocessor architecture for ubiquitous AI—An overview on history, evolution, and upcoming challenges in AI implementation. *Micromachines* **2021**, *12*, 665. [[CrossRef](#)]
22. Kwack, J.; Tramm, J.; Bertoni, C.; Ghadar, Y.; Homerding, B.; Rangel, E.; Knight, C.; Parker, S. Evaluation of performance portability of applications and mini-apps across amd, intel and nvidia gpus. In Proceedings of the 2021 International Workshop on Performance, Portability and Productivity in HPC (P3HPC), St. Louis, MO, USA, 14 November 2021; pp. 45–56.
23. Cerrolaza, J.P.; Obermaier, R.; Abella, J.; Cazorla, F.J.; Grüttner, K.; Agirre, I.; Ahmadian, H.; Allende, I. Multi-core devices for safety-critical systems: A survey. *ACM Comput. Surv. (CSUR)* **2020**, *53*, 1–38. [[CrossRef](#)]
24. Wu, B.; Wu, X.; Li, P.; Gao, Y.; Si, J.; Al-Dhahir, N. Efficient FPGA Implementation of Convolutional Neural Networks and Long Short-Term Memory for Radar Emitter Signal Recognition. *Sensors* **2024**, *24*, 889. [[CrossRef](#)] [[PubMed](#)]
25. Heo, J.; Jung, Y.; Lee, S.; Jung, Y. FPGA implementation of an efficient FFT processor for FMCW radar signal processing. *Sensors* **2021**, *21*, 6443. [[CrossRef](#)] [[PubMed](#)]
26. Li, W.; Tang, C.; Vishwakarma, S.; Woodbridge, K.; Chetty, K. Design of high-speed software defined radar with GPU accelerator. *IET Radar Sonar Navig.* **2022**, *16*, 1083–1094. [[CrossRef](#)]
27. Rifai, S.; Vincent, P.; Muller, X.; Glorot, X.; Bengio, Y. Contractive auto-encoders: Explicit invariance during feature extraction. In Proceedings of the 28th International Conference on Machine Learning, Bellevue, WA, USA, 28 June–2 July 2011; pp. 833–840.
28. Mao, A.; Mohri, M.; Zhong, Y. Cross-entropy loss functions: Theoretical analysis and applications. In Proceedings of the 40th International Conference on Machine Learning, PMLR, Honolulu, HI, USA, 23–29 July 2023; pp. 23803–23828.
29. Kingma, D.; Ba, J. Adam: A Method for Stochastic Optimization. *arXiv* **2014**, arXiv:1412.6980.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.