Deep Transfer Learning for Array Failure Diagnosis

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This is one of the optional topics for my undergraduate final year project. Since I didn't have enough knowledge in machine learning at that time, I chose another topic. But after I took these machine learning courses(697AM and 697ML), I felt like I could pick up the topic again.

CATALOG

1.Introduction

Array antennas are widely used in modern radar equipment due to their high power, high gain, and fast beam scanning. The structure of the array antenna is complex, and the failure of the array element is not easy to replace and repair, especially in the aerospace, battlefield, and other application environments. Therefore, it is particularly important to analyze the effect of the failed array element on the performance of the array antenna and to quickly locate the failed array element under limited conditions.

To solve the problem of a large amount of labeled data time-consuming training procedure, this project aims to an array diagnosis method based on deep transfer learning which transfers knowledge from the trained diagnosis model to other arrays with different structures to accelerate the diagnosis model training using a small set of training data and maintain satisfactory diagnosis accuracy. Firstly, an array failure diagnosis model based on DNN is trained as the base model. Secondly, an end-to-end deep transfer network is built for failure diagnosis of other arrays by dividing the target domain into several sub-domains and reusing the base model multiple times. Then, the parameters of the diagnosis model are carefully tuned using small far-field radiation data of the target domain. Finally, computer simulations(Tensorflow, Keras) are conducted to verify the validity and superiority of the proposed method

2.Linear Base Model

Consider a linear array with L elements located at $d_i (i = 1, \ldots, L)$. The observed far-field radiation data of the array at θ_m concerning the normal direction can be expressed as

$$z(\theta_m) = \sum_{i=1}^{L} e^{j\frac{2\pi f d_i \sin(\theta_m)}{c}} x_i + n_m$$

where c denotes the speed of light, f is the operating frequency of the antenna array and x_i indicates the excitation of the ith array element, n_m is the measurement noise of radiation data at θ_m.

If the array is a planar array with K elements, where d_i^x and d_i^y are the coordinates of the ith element, the observed far-field radiation pattern of a planar array at elevation angle θ_m and azimuth angle ϕ_w can be expressed as

$$\psi(m, w) = d_i^x \sin(\theta_m)\cos(\phi_w) + d_i^y \sin(\theta_m)\sin(\phi_w)$$

$$z(\theta_m, \phi_w) = \sum_{i=1}^{K} e^{j\frac{2\pi f \psi(m,w)}{c}} x_i + n_{(m,w)}$$

From the above equations, we can know it is a complicated non-linear relationship between the radiation data of the array and the locations of elements. Assuming that the excitation of failing elements is zero, the locations of failing elements can be determined by the estimated excitation. Taking the radiation data as features and the indicators of elements as labels, a classifier can be trained to determine the locations of failing elements.

Because of the simple structure of linear arrays, the diagnosis model of a linear array is taken as the base model. Since the radiation data Z_s^i is a complex vector containing M elements, the real part of the vector is taken as the input of the first M neurons and the imaginary part is taken as the input of M + 1 to 2M neurons. Taking the failing indicators of elements Y_s^i as output, a DNN classifier can be trained, which is expressed as

$$Y_s = f_s([Re(Z_s), Im(Z_s)])$$

Assuming that each array element failure is independent, the binarcross-entropypy is chosen as the loss function and sigmoid is chosen as the activation function of the last layer, which enables the value of each output neuron of this DNN to be between 0 and 1. If the output is smaller than 0.5, the corresponding element is considered to be failing, otherwise, the element works well. Denoting t as label and $\hat{t}$ as prediction, binary cross-entropy is given by

$$L_{Binary-cross-entropy} = -tlog\hat{t} - (1-t)\log(1-\hat{t})$$

The following table shows the specific configuration of this basic neural network：

TABLE I

HYPERPARAMETERS OF THE BASE MDEL FOR LINEAR ARRAY FAILURE DIAGNOSIS

Layers	**Number of neurons/ Dropout rate**	**Activation function**
Input layer	182	*relu*
Fully connect layer	128	*relu*
Fully connect layer	80	*relu*
Fully connect layer	64	*relu*
Dropout	0.2	
Fully connect layer	64	*sigmoid*

3.Deep Transfer Model

A deep transfer network for planar array failure diagnosis is proposed in this section, which is shown in Fig. 1. The framework consists of three parts: domain division, model transferring, and fine-tune.

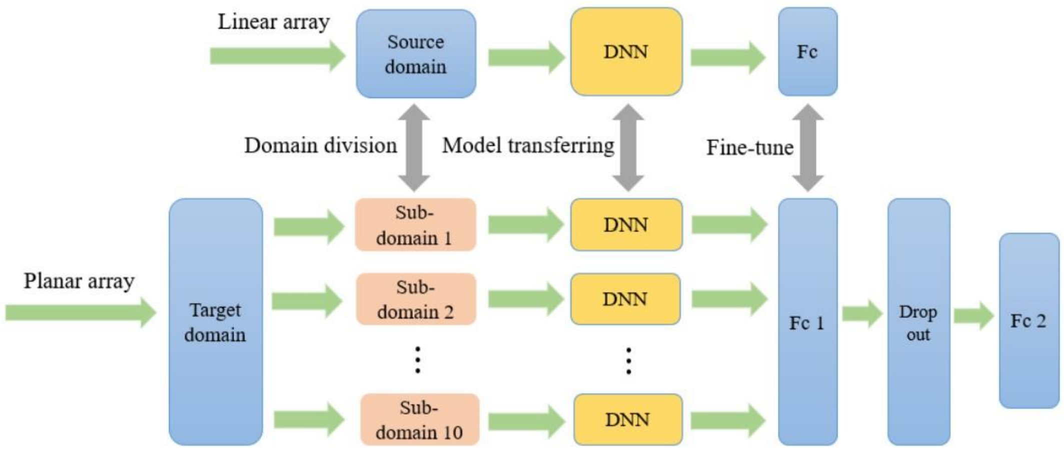

Fig.1 Framework of the proposed deep transfer network for planar array failure diagnosis (Fc is an abbreviation for Fully connect layer.)

(1) Domain division is to divide the target domain into several subdomains, each of which has the same dimensions as the dimensions of the source domain. Since the radiation data of the planar array is measured concerning elevation and azimuth angle and the linear array is only measured concerning elevation angle, the number of sub-domains is equal to the number of azimuth angles. The reason for the way of division is the radiation data of linear arrays can be considered as being measured from the same azimuth angle, while planar arrays are measured from different azimuth angles. The radiation data measured from each azimuth angle is considered a sub-domain.

(2) The proposed deep transfer network framework is a kind of a network-based transfer learning framework. It is based on the assumption that the neural network is similar to the abstraction process. The front layers of the network can be treated as a feature extractor and the extracted features are universal. Model transferring is to transfer knowledge from the trained base model for linear arrays to planar arrays. Since the last layer of a deep network is to make the final decision, the proposed deep transfer model for the planar array reuses the layers of the base model except for the last layer.

(3) Fine-tune is a usual technique for deep transfer learning. There are two kinds of normal operations for fine-tuning: one is to freeze the parameters of the transferred model and only train the parameters of newly added one or two layers and the other is to train all parameters on the target domain. In the proposed framework, two new layers are added and all parameters of the whole deep transfer network are trained using small radiation data of a planar array. Since each sub-domain can determine a set of failing elements locations of the same planar array, the added layers can be also considered as the weighted combination of all the set of failing elements locations determined by each sub-domain. Intuitively, the diagnosis accuracy determined by a weighted combination of multiple diagnosis results is higher than a direct diagnosis result.

4.Model Visualization

Through Tensorboard visualization, the flow chart of the traditional DNN diagnosis model and the deep migration model can be generated, to easily observe the changes of input and output and the relationship between each layer:

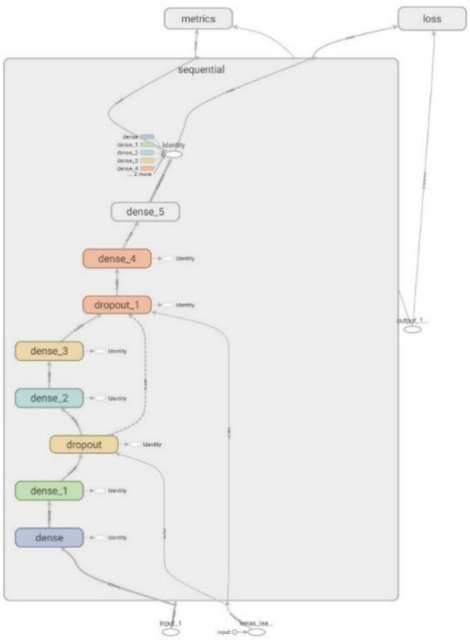

Fig.2 Traditional DNN Model

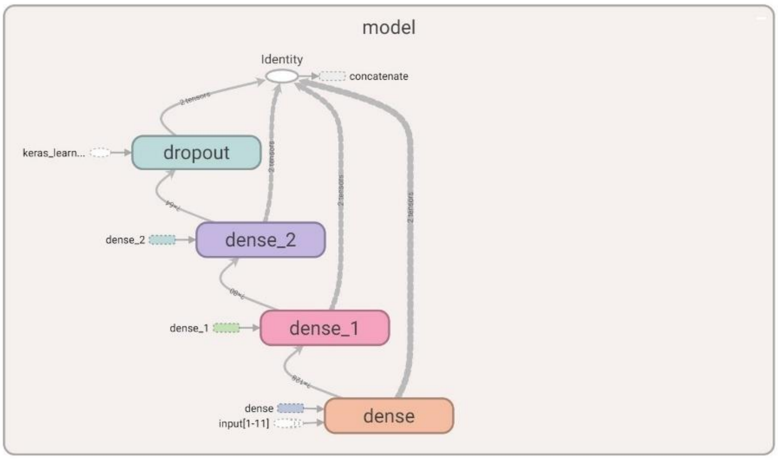

Fig.3 Base Diagnosis

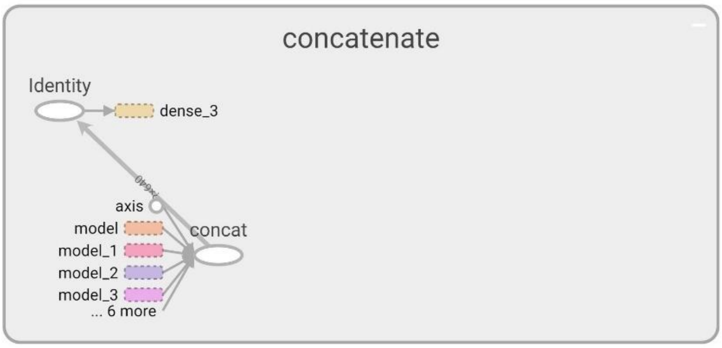

Fig.4 Subdomain Fusion Layer

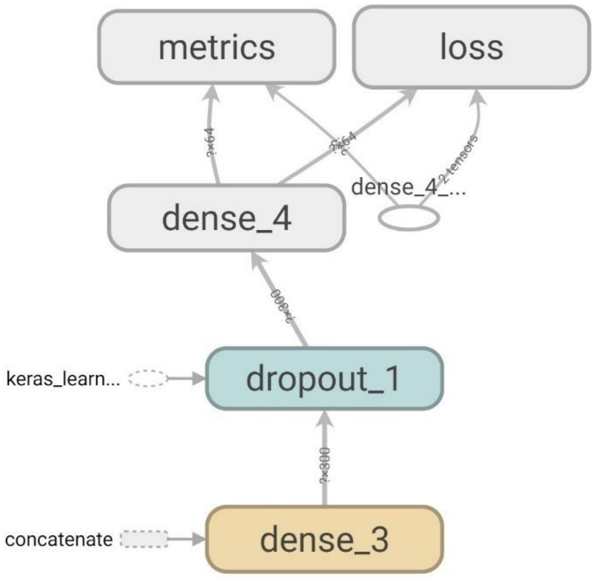

Fig.5 Deep Transfer Network

5.DataSet and Evaluation Test

The pattern dataset is sampled from -90 to 90 degrees at 2-degree elevation angle intervals and from 0 to 180 degrees at 20-degree azimuth angle intervals. Therefore, the dimension of the far-field pattern is 910. After separating the real part and the imaginary part, the dimension becomes 1820. As for the label, it should be a 64-dimensional array failure indicator vector. A value of 1 means no failure, and 0 means failure.

All data were normalized to remove bias between data in each dimension.

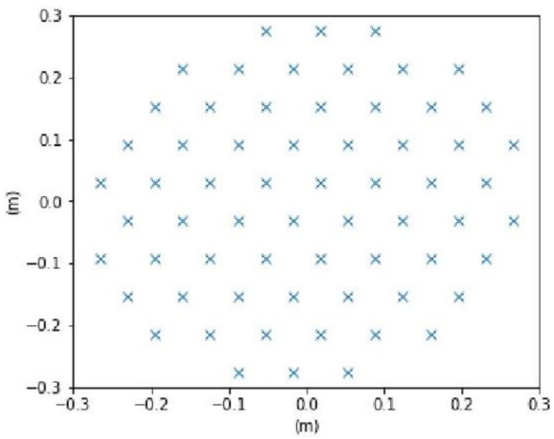

Fig. 6 The structure of the real-world planar array with 64 elements (blue crosses denote locations of array elements)

The array to be diagnosed is the 64-element planar antenna array as shown in Fig.6 above. Considering that there are no more than 7 failed units, use the far-field pattern to diagnose the array antenna. The output label is a 64-dimensional binary vector.

It is estimated that the number of samples should be around 8,000(this may change). There should be 8 different failure situations caused by man (the number of failed array elements is 0 to 7), and 1,000 samples should be sampled for each failure situation. 80% of the dataset is randomly selected as training data and the rest as testing data. All data were normalized to remove bias between data in each dimension.

First, number each mode, because there are 8 failure cases (including no failure), and each case has 1000 instances of far-field patterns randomly, so there are 8000 modes in total, and the failure array element diagnosis is regarded as multi-class multi-label and the problem needs to be divided into 8000 categories.

I contacted the senior at my undergraduate school, he is very willing to provide me with relevant data sets. As long as my proposal is approved by the professor, my senior will make an appointment to go to the Array Antenna Lab to collect data. I would like to express my special thanks to him.

The neural network model built for this problem is shown in Figure 7. To extract the main features of the input, the CNN convolutional layer is first reused 3 times, then the overfitting is weakened by the Dropout layer, and then the dimension of the output value is changed to be equal to the dimension of the label through the two fully connected layers. In the multi-label multi-classification problem, each array element is independent of failure or work, so Sigmoid is used as the activation function of the output layer; greater than 0.5 is regarded as work, otherwise, it is invalid.

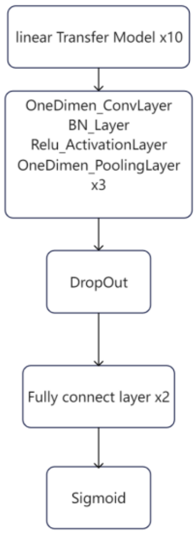

Fig.7 Transfer Network Structure

During the training process, the sample data is the far-field pattern of 8000 cases. The optimization algorithm in training uses Adam, where the step size $\in$=0.01, the exponential decay rates ρ_1 and ρ_2 are 0.9 and 0.999, respectively, the numerically stable constant δ=10^(-8), the sample per batch is 50, and the cost function uses Cross Entropy.

First, it is necessary to verify the effectiveness and feasibility of the constructed deep transfer network for array diagnosis. Figures 8 and 9 below show the performance of the transfer network on randomly sampled training and test sets. It can be seen from the figure that with the increase of the number of training rounds, the Cross Entropy Error (CEE) between the reconstructed excitation and the real excitation is generally decreasing and the diagnostic accuracy is close to 1. Even if there are some fluctuations in training, it recovers quickly, proving the feasibility of deep transfer model building.

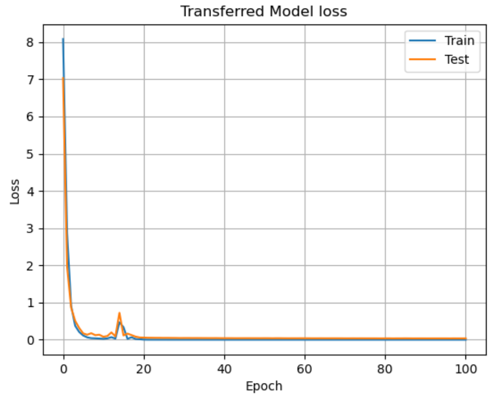

Fig.8 The Error of the Transfer Network on Train and Test Sets

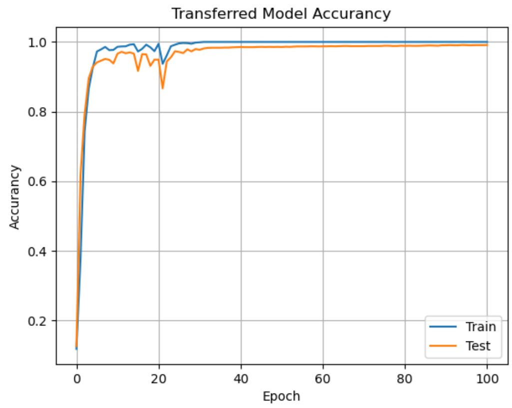

Fig.9 Diagnostic Accuracy of Transfer Networks on Train and Test Sets

Figures 10 and 11 below show the performance of the traditional DNN model and the newly constructed transfer model on the training set and test set, respectively. As can be seen from the figure, compared with the traditional DNN model, the deep transfer network can use less time to achieve better results. No matter on the training set or the test set, the deep transfer network uses a shorter time to achieve lower error and better diagnostic accuracy; but because the training set has more samples, so the performance on the training set Both are better than the performance on the test set, which is predictable. Therefore, it is proved that the transferred new network has better diagnostic performance than traditional DNN.

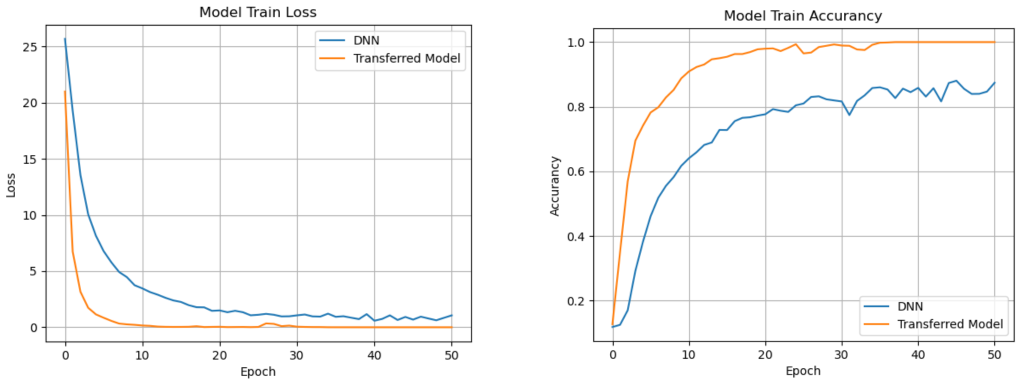

Fig.10 Loss and accuracy of the two models on the training set

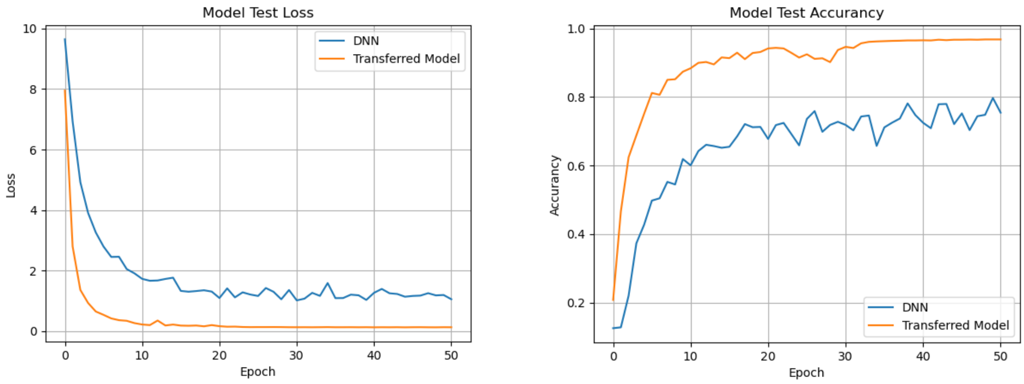

Fig.11 Loss and accuracy of the two models on the test set

After evaluating the loss and accuracy, this section also counts the number of correctly diagnosed samples in each failure condition in the test set; only when each neuron at the output matches the label, it is considered correct, otherwise it is a failure . As shown in Figures 12 and 13 below.

There are a total of 2400 samples in the test set, 300 samples for each failure case, and a total of eight failure cases.

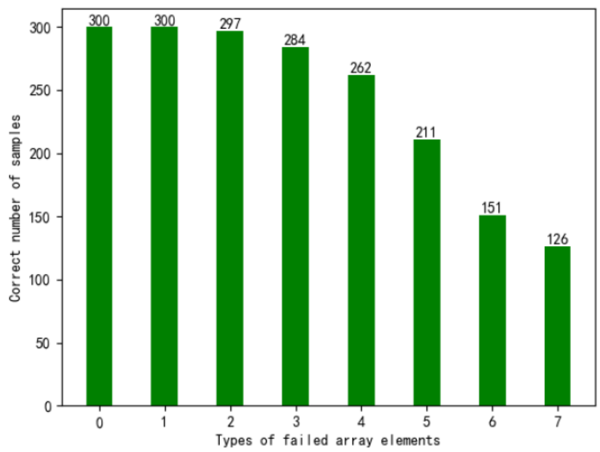

Fig.12 30% training set diagnostic performance

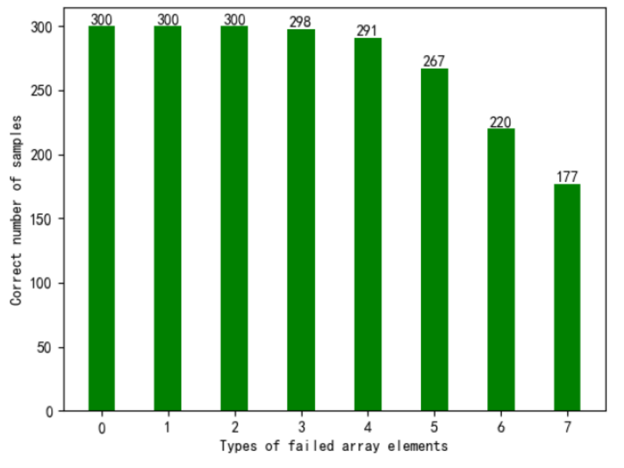

Fig.13 80% training set diagnostic performance

It can be clearly seen from the above figure that the size of the training set and the number of failed array elements have a significant impact on the number of correct samples for diagnosis. When the training set increases, the number of correctly diagnosed samples in each case of failed array elements increases; and no matter which training set is used, the more the array elements fail, the less the number of correctly diagnosed samples; this It also means that the case of a large number of failed array elements is more difficult to train than the case of a small number of failed array elements, and the network is more difficult to form, resulting in a smaller number of correctly diagnosed samples.

7.Conclusion

This report firstly introduces the effect of element failures in antenna arrays on the radiation performance of antennas, and then proposes a new deep transfer learning framework for the diagnosis of failed antenna elements. Compared with the existing machine learning diagnosis methods, this method can accurately realize diagnosis with less training data by transferring some knowledge in the trained base model; consumes less time, and has higher accuracy.

Overview, the research content and the work of this report are as follows:

1. The influence of the array failure in the antenna array on the pattern is analyzed;
2. Researched how to use the line array basic network to perform domain partitioning on planar arrays and build deep transfer networks
3. Design reasonable learning and weight update rules for simulation, which verifies

the feasibility of the method for diagnosing failed components.

Current areas for improvement and prospects for future work:

1. The application of transfer learning in the array element failure diagnosis model still needs to be optimized. Overfitting still exists. Should regularization be added to deal with overfitting? Whether the dynamic change of the optimizer's learning rate has better simulation performance? These issues have not been considered.
2. Extending the application of diagnostic algorithms to other forms of larger arrays is also a direction that should be considered and carried out.

References

[1] G. Oliveri, P. Rocca, and A. Massa, “Reliable diagnosis of large linear arrays—A Bay esian compressive sensing approach,” IEEE Trans. Antennas Propag., vol. 60, no. 10, pp. 4627–4636, Oct. 2012.

[2] H. Zhao, Y. Zhang, J. Hu, and Z. Chen, “Hybrid sparse reconstruction method of mo ments for diagnosis of wire antenna arrays,” Applied Computational Electromagnetics Society Journal, vol. 32, no. 10, pp. 882-887, Oct 2017.

[3] Y. Zhang and W. Wang, “Robust Array Diagnosis Against Array Mismatch Using A mplitude-Only Far Field Data,” in IEEE Access, vol. 7, pp. 5589-5596, 2019.

[4] Oliveri, Giacomo , P. Rocca , and A. Massa . “Failure detection in large arrays throu gh bayesian compressive sensing.” European Conference on Antennas & Propagation I EEE, 2013

[5] H.Zhao,Y.Zhang,E.-P.Li,A.Buonanno,andM.D’Urso, “Diagnosisof array failure in impulsiv enoise environment using unsupervised support vector regression method,” IEEE Trans. Antennas Propag., vol. 61, no. 11, pp. 5508-5516, Nov 2013.

[6] A. Patnaik, B. Chowdhury, P. Pradhan, R. K. Mishra, and C. Christodolou, “An ANN application for fault finding in antenna arrays,” IEEE Trans. Antennas Propag., vol. 5 5, no. 3, pp. 775–777, Mar. 2007.

[7] N. V. S. N. Sarma and D. Vakula, “A Method for Diagnosis of Current Faults in Ant enna Arrays Using Neural Networks,” International Journal of RF and Microwave Co mputer-Aided Engineering, 2008.

[8] D. Vakula and N. Sarma. “Neural network approach to diagnose phase shifter faults of antenna arrays.” International Conference on Electromagnetic Interference & Compatibi lity IEEE, 2006.

[9] Tan, Chuanqi , et al. “A Survey on Deep Transfer Learning.” (2018).