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VEHICLES CLASSIFICATION BASED ON DIFFERENT COMBINATION OF FEATURE EXTRACTION ALGORITHM WITH NEURAL NETWORK (NN) USING FORWARD SCATTERING RADAR (FSR)

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ABSTRACT

Feature extraction process plays an important role in classifying radar target. The extracted features will be fed as the input to the classifier. The incorrect choice of extracted features will cause poor performance of radar classification system. This paper presents the vehicles classification based on combination of different feature extraction algorithm with neural network using forward scattering radar. Hence, the main objective of this paper is to analyze the most suitable feature extraction algorithm which based on different dimensionality reduction technique in order to evaluate the performance of classification system. Three different techniques are used such as the manual and automatic reduction technique (PCA and Z-score) and neural network as classifier to classify the vehicles into their groups either medium or large based on their physical size. The performance of the classification system is determined by the percentage of classification accuracy. The higher percentage of the classification accuracy shows the better performance of the classification system.

Keywords: *Neural Network (NN), Forward Scatter Radar (FSR), Principal Component Analysis (PCA), Z-score,Classification Accuracy (CA)*

1. INTRODUCTION

Forward scatter radar (FSR) system is known as a special case of bistatic radar [1-4]. In such radar, the antenna of receiver and transmitter are fixed and directed at each other [5], thus the target detection takes place only when the target is crossing the baseline. Past years, studies on FSR micro-sensor network on ground have been carried out by a research group in Birmingham University [6, 7] . The main purpose of FSR micro-sensor network is for situational awareness where it is used to recognize and detect the ground target such as vehicles or personnel entering or crossing the network coverage area [5, 7-11].

There are number of researches that have been done specifically in classifying the targets using FSR. The earliest research on ground target classification using FSR was done by R. Abdullah et al. 2003. [13]. The researchers classified four different types of vehicles into their categories based on their sizes and types at frequency 1GHz in ideal case scenario where the vehicle is crossing the baseline perpendicularly. In order to perform the vehicles classification, the combination of principal component analysis (PCA) and k-nearest neighbor (KNN) was proposed. The results obtained shows that good vehicles classification performance can be achieved.

The same classification method was applied in [14] but with different trajectory known as angle of

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detection. Theoretically, target's trajectory is one of the factors affecting the target's signature which contributes towards the poor performance of the classification system. Hence by using multiple sensors, the discrepancies in classification performance could be reduced. Later, the same classification system has been tested at low frequencies: Ultra High Frequency (UHF) and (Very High Frequency (VHF) band [9]. The paper proved that a good classification performance can be obtained even at low frequency.

For a performance comparison purposed, neural network (NN) has been introduced as a classifier [15]. The input of NN is defined as a length of vehicle and back-propagation neural network (BPNN) is used as a neural network model. The paper proves that NN is suitable to be used as a classifier since the classification accuracy exceeds more than 90% of true classification.

Later, the improvement of the above technique has been reported in [16]. The input of NN is extracted from the target's signature. The researchers used the main lobe width, second main lobe and number of lobes as the inputs of NN. The multi-layer perceptron (MLP) is applied to train the network. By applying this technique, a better classification performance can be achieved.

However the performance of classification system is still below satisfaction level especially under the influence of external factors such as clutter [5] and target trajectories uncertainties [12] and features use as the input to the classifier.

More accurate classification algorithm should be integrated with features extraction algorithm based on dimensionality reduction technique to further improve the accuracy of the latter. Hence, in this paper, three different dimensionality reduction techniques which are manual and automatic (PCA and Z-score) have been chosen in order to evaluate the performance of the classification system for three different frequencies: 64 MHz, 151 MHz and 434.

2. CLASSIFICATION SYSTEM

Figure 1 shows the proposed ground target classification system.

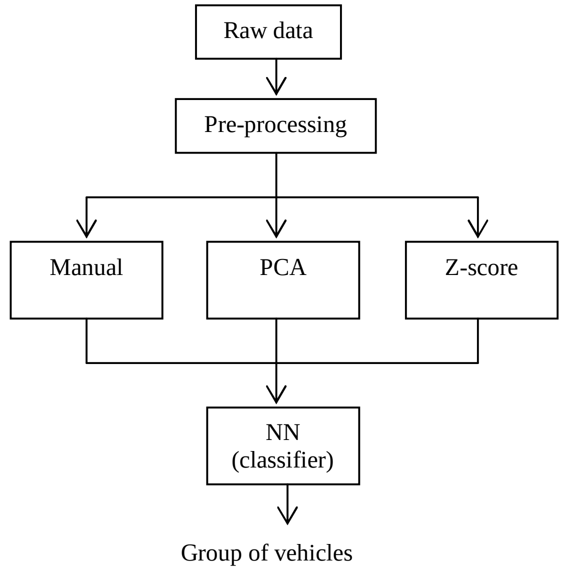

Figure 1: The Proposed Classification System of Vehicles Classification

The received signal needs to be transformed into a frequency domain signal by using Fast Fourier Transform (FFT) method. By transforming the signal, the similarities and differences between the vehicles become more visible. Prior to that, the signal needs to be filtered, calculated its power spectrum and normalized in terms of power and speed of the target. This processed signal is then passed through to the classification process where the features of the signal will be dimensionality reduced, extracted and later classified. The features of the signal can either manually or automatically extract based on different dimensionality reduction technique such as PCA and Z-score. The extracted features become the input of the classifier. The selection of feature reduction technique and classifier is highly dependent on the target's signature and must be able to classify the vehicles into their group based on the size of vehicles.

3. DIMENSIONALITY REDUCTION TECHNIQUE

Feature extraction is a technique used to extract an important feature contain in the signal. For some cases, classification can be done in the reduced space more accurately than the original space. For high dimensional datasets like the one that we have, dimension reduction is advisable prior to any

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classification process in order to avoid the effects of the curse of dimensionality. The accuracy of the classification system is highly dependent on the chosen technique.

3.1 Manual technique

Target's features are extracted manually; hence any information from the recorded signal will be used as the input to the Neural Network. The information's are baseline length, crossing point, crossing angle, speed and the target signal itself.

3.2 Principal Component Analysis (PCA)

PCA can be categorized as an automatic feature selection especially in the area of image compression, face recognition, weather prediction and target recognition [17]. PCA is selected due to its ability to identify patterns in data and expressing the data to their similarities and differences. Since the data are in high dimension; PCA is a powerful tool to reduce the dimensionality of data in order to avoid the high losses of information. To perform PCA, there a several steps that need to be conducted:

i. Find the mean of given sets of signals feature vectors.

$$X_{mean} = \frac{\sum_{i=1}^{M} x_i}{M} \quad (1)$$

where x_i is a feature vector and n is number of vector

ii. Subtract the mean feature vector from each vector. This produces a data set whose mean is zero.

$$R = x_i - X_{mean} \quad (2)$$

iii. Calculate the covariance matrix, S

$$S = \frac{\sum_{i=1}^{M}(xi - X_{mean})(xi - X_{mean})}{M-1} \quad (3)$$

iv. Calculate the eigenvector and eigenvalue of the covariance matrix $(S-\lambda_1 I)\ e_1 = 0$ where e_1 is represent the eigenvector while λ_1 indicate the eigenvalue.

v. Choosing components and forming a feature vector.

$$W = [e_1; e_2; e_3; \ldots ;e_p] \quad (4)$$

vi. Deriving the new data set.

$$New\ data = W^T \text{ x } R \quad (5)$$

vii. Find the number of principal components (PCs).

The number of PCs depends on the amount of variance of the data. The first PC indicates the largest amount of variance in the data then the second PC represents the second largest amount of variance and so on. Only the first few PCs are necessary to indicate the information contained within the data. There is no mathematical calculation needed to obtain the number of PCs needed. However, we can use percentage of variance for example above 80% as a reference or benchmark.

Figure 2 (a), (b) and (c) illustrate the variance and cumulative variance described by a given principal component for frequency 64, 151 and 434 MHz. In this paper, we only considered the number of PCs which is above the variance of 80%.

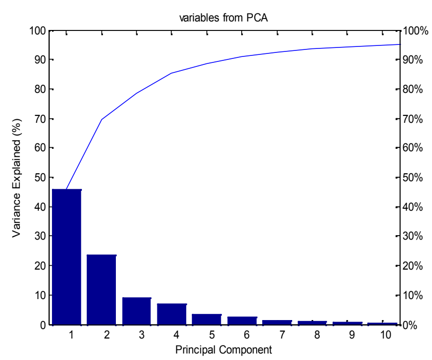

Figure 2 (a): Variance and Cumulative Variance Described by a Given Principal Component for Frequency 64 MHz

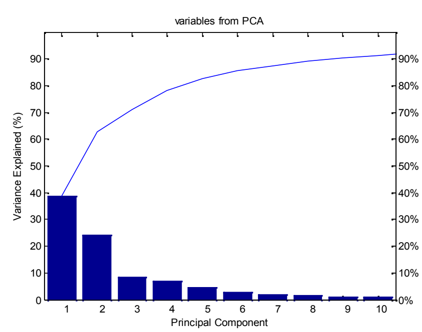

Figure 2 (b): Variance and Cumulative Variance Described by a Given Principal Component for Frequency 151 MHz

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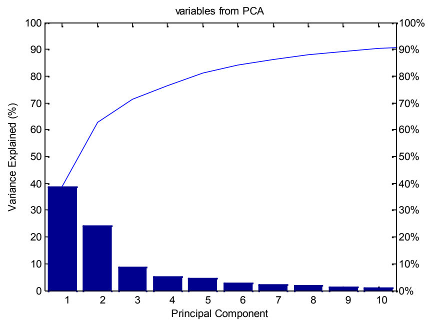

Figure 2 (c): Variance and Cumulative Variance Described by a Given Principal Component for Frequency 434 MHz

3.3 Z-Score

Z-score is known as a standard score which mean the number of standard deviation an observation. In Z-score rule, there are positive and negative values. The positive value will represent data which is above the mean while the negative value indicates data below the mean value. In order to calculate the value of z-score, several steps need to be followed:

i. Data collection

It is important to have a large number of data to make sure that all reasonable variations from the average values are covered.

ii. Calculate the mean of value of data, X_{mean}

$$X_{mean} = \frac{a}{b} \quad (1)$$

where a indicate total values of data while b act as number of data.

iii. Calculate the standard deviation, σ

This represent how tightly and loosely the values are grouped around the mean.

iv. Calculate the value of Z-score, z

$$z = \frac{x - X_{mean}}{\sigma} \quad (2)$$

where x indicate the value of data.

v. Data Selection

Data need to be divided between positives and negatives values of Z-score. Only data with positive values of Z-score will be considered as a significant data and become an input to NN.

4. NEURAL NETWORK AS CLASSIFIER

NN are known as non-linear mapping structures based on the function of the human brain. It is machine learning with number of neurons. The neurons in NN tend to have fewer connections than biological neuron. Therefore, NN can identify and learn correlated patterns between input data and corresponding to the target values. After training, NN can be used to predict the outcome of new independent input data and highly used in prediction and classification system where the regression model has been employed. There are various type of NN like MLP, Radial Basic Function (RBF) and Kohonen networks.

i. Development of NN model

NN is constructed with many layers and thus termed as multilayer neural network. The first layer represents the input units. These units can be known as independent variables. The last layer indicates the output units. For these units, there are known as dependent variable. Each layer in NN consists of neurons where those neurons are linked together. The activation function can be used in network configuration to specify the input range. There are three types of activation function in NN for example, logsig, tansig and purelin.

ii. Variables selection

The input variables are important for vehicles classification. Feature extraction process provides the input to NN. As mentioned above, two types of automatic selection (PCA and Z-score) and also a manual selection are used. Manual selection is used as a benchmark to evaluate the performance of automatic selection process.

iii. Training and testing data

The set of data are divided into training and testing processes. The purpose of training phase is to train the network while the testing process is to evaluate the network performance. The division of data is 80% for training and 20% for testing. As mentioned in [18], the training data must exceed the number of testing data.

iv. NN architecture

NN architecture network can be grouped into two categories: feed forward and back forward network. The feed forward network is also known as MLP which consists of an input layer of neurons, one or more hidden layer and an output layer of computational neurons. Figure 3 demonstrates the architecture of multi-layer feed forward network. In feed forward network the signals are only travelling in one direction; from input to hidden layer and to output layer (no feedback or loop occurs in the network). Therefore this kind of architecture is

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extensively used in pattern recognition and classification and is chosen for this study.

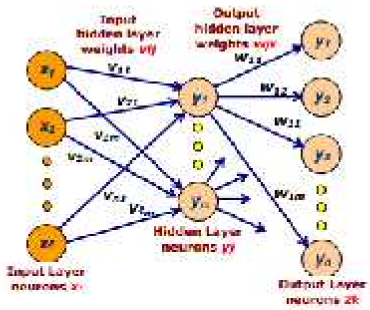

Figure 3: Architecture of Multi-Layer Feed Forward Network

v. Supervised learning

There are two types of learning in NN such as supervised and unsupervised learning. In this paper, supervised learning is selected since it defines the effect of input to the output and the system that we used has desired output.

vi. Back-propagation algorithm

The back propagation algorithm consists of six steps:

a. Initialize the weight to small random values
b. Randomly choose input pattern $X^{(\mu)}$
c. Propagate the signal forward through the network
d. Compute δ_i^L in the output layer $(o_i = y_i^L)$
e. Compute the δ for the preceding layers by propagating the errors backwards
f. Update weights

5. EXPERIMENTAL SET-UP DESCRIPTION

The data for vehicles classification are obtained from the experiment. The experiment was held at empty car park. The experimental set-up can be seen in Figure 4 where the baseline (distance between transmitter and receiver) was 50m. The baseline can be achieved up to 200-300m in practice as mentioned in [9]. The use of transmitter in this experiment is to transmit the signal in all three frequencies simultaneously. The receiver recorded the signature of four different cars moving perpendicular to transmitter and receiver.

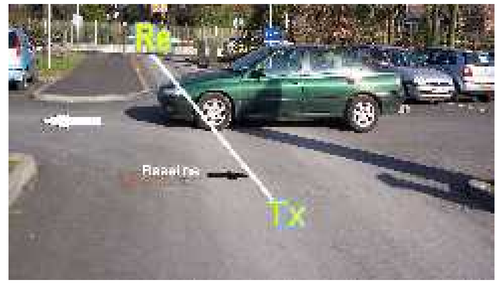

Figure 4: Experimental Set-up

6. RESULTS AND DISCUSSION

The total numbers of targets signals for each frequency are 200 targets signals as presented in Table 1. Four different types of car with different dimensions are used. The results are presented for three different feature extraction techniques:

1. Manual extraction
2. Automatic feature extraction using PCA
3. Automatic feature extraction using Z-score

Table 1: Total Target Signals before Extraction

Frequencies used (MHZ)	Types of ground vehicles used				Total signals
	A	B	C	D	
64	50	50	50	50	200
151	50	50	50	50	200
434	50	50	50	50	200

6.1 Manual Extraction

Figure 5 shows the classification results obtained from extracting the target's feature manually. As can be seen in Figure 5 (a), (b) and (c) there is no false target classified by NN. Therefore the accuracy of classification for training data achieved 100% true classified. The results of classification of testing data are presented in Figure 5 (d), (e), and (f). The classification accuracy for testing data drops from 100% to 90%. The results of classification accuracy results are tabled in Table 2.

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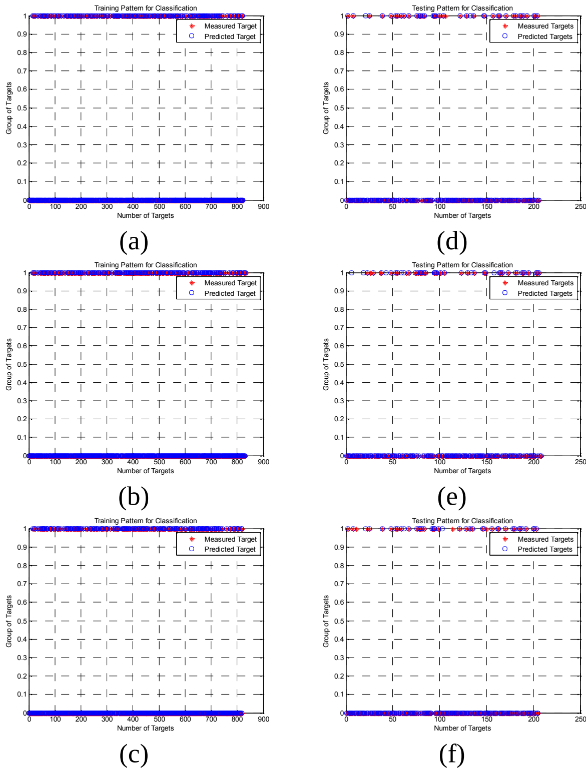
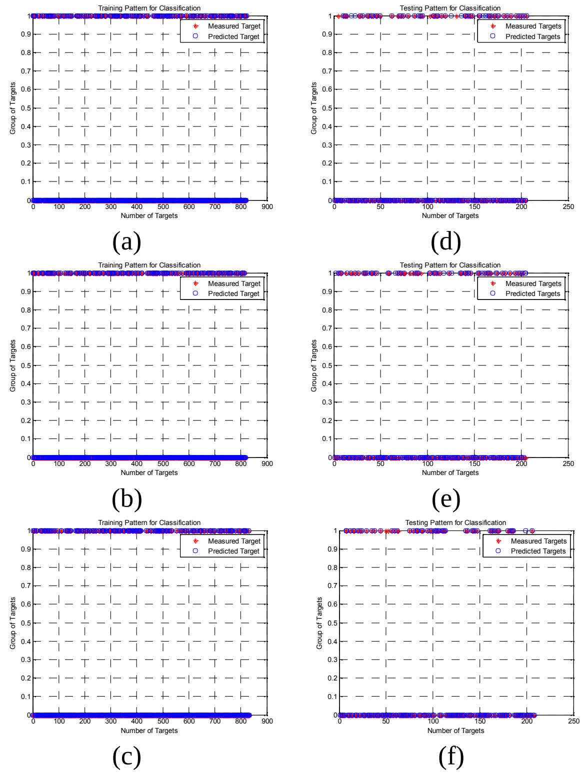


(a) (d) (b) (e) (c) (f)

Figure 5: Classification results when manual extraction is applied for training data (a) at 64 MHz, (b) at 151 MHz and (c) at 434 MHz; testing data (d) at 64 MHz, (e) at 151 MHz and (f) at 434



(a) (d) (b) (e) (c) (f)

Figure 6: Classification results when PCA is applied for training data (a) at 64 MHz, (b) at 151 MHz and (c) at 434 MHz; testing data (d) at 64 MHz, (e) at 151 MHz and (f) at 434

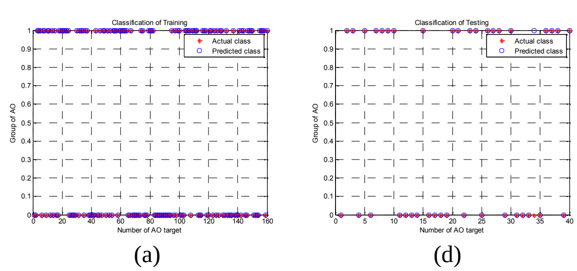
6.2 Principal Component Analysis (PCA)

In PCA principle, number of PC is one of the important factor need to be considered prior to the classification process. As stated in [13, 19, 20] data are usually presented by only the first few PCs numbers. In this case, the first five numbers of PCs which reflect more than 95% of the variance of data are chosen.

Figure 6 (a), (b) and (c) show the training pattern for classification at 64 MHz, 151 MHz and 434 MHz. The plots show the measured and predicted data are overlapping to each other which reflect the 100% true classification. While, for testing data, the results obtained are inconsistent since there are some misclassified targets. The classification accuracy for testing data drastically drops from 100% to 90% at frequency 151MHz. The results of classification accuracy for each frequency are tabulated in Table 3.

6.3 Z-Score

Figure 7 illustrate the classification results when Z-score is applied. In Figure 7 (a), (b), and (c) it can be seen that data for each frequency for training phase are overlapping and gives 100% classification accuracy. The results of NN testing are presented in 7 (d), (e) and (f). Due to the few misclassified targets at frequency 434 MHz, the accuracy decreased from 100% to 93%. The results of classification accuracy for this technique are summarized in table 4.



(a) (d)

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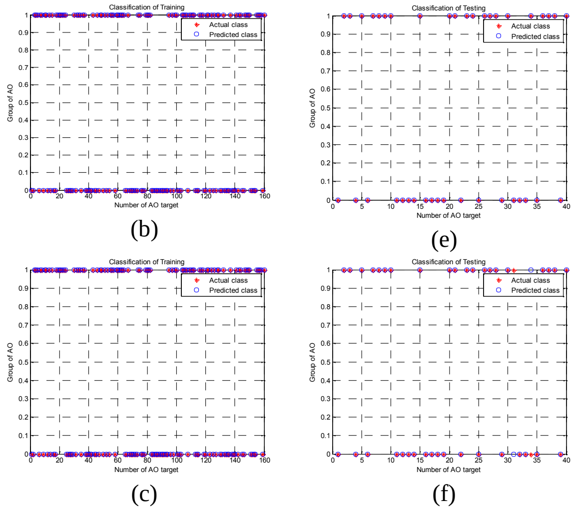

Figure 7: Classification results when Z-score is applied for training data (a) at 64 MHz, (b) at 151 MHz and (c) at 434 MHz; testing data (d) at 64 MHz, (e) at 151 MHz and (f) at 434

Figure 8 shows the pattern of classification results for three different techniques of feature extraction by using NN. From Figure 8, we can see at frequency 64 MHz and 151MHz, the classification system combination of Z-score with NN gives higher classification which is 100% accuracy compares to the other two classification systems. However, at frequency 434 MHz the classification accuracy decreases to 93%. This result is in contrast to the usual optical presentation of forward scattering nature which requires the system wavelength to be shorter than characteristic dimensions of the target shape for the reliable target classification. This can be explained by the presence of clutter, which is stronger at 434 MHz than at 64 and 151 MHz.

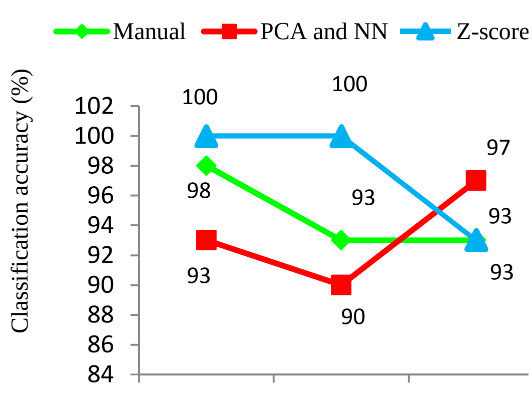

Figure 8: The Classification Accuracy for Each Frequency

7. CONCLUSION AND FUTURE WORKS

In this paper, we have presented the analysis of classification performance using the combination of manual and automatic feature algorithm (PCA and Z-score) with neural network. From recent works [15, 16], it can be seen that the highest classification accuracy for group of vehicles achieved 90% true classification when using the classification technique of manual feature extraction and NN. However, by using the above suggested classification technique, the combination of Z-score and NN gives the best classification performance especially at 64 MHz and 151 MHz compared to manual selection and PCA. It is suggested that an optimization technique should be applied especially at 434 MHz in order to improve the classification accuracy.

For future works, it is recommended that bigger database will be required in order to improve the classification performance. Other than that, the classification system also can be tested with real case scenario by adding the clutter environment.

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Table 2: Performance of classification with combination of manual extraction and NN

Parameter (%)	Classification					
	Training data			Testing data		
	64 MHz	151 MHz	434 MHz	64 MHz	151 MHz	434 MHz
Accuracy	100	100	100	92	93	95
Precision	100	100	100	95	94	96
Sensitivity	100	100	100	95	98	98
Specification	99	98	100	82	78	83

Table 3: Performance of classification with combination of PCA and NN

Parameter (%)	Classification					
	Training data			Testing data		
	64 MHz	151 MHz	434 MHz	64 MHz	151 MHz	434 MHz
Accuracy	100	98	100	98	90	97
Precision	100	98	100	93	99	92
Sensitivity	100	100	100	93	97	87
Specification	99	95	100	82	98	77

Table 4: Performance of classification with combination of Z-score and NN

Parameter (%)	Classification					
	Training data			Testing data		
	64 MHz	151 MHz	434 MHz	64 MHz	151 MHz	434 MHz
Accuracy	100	100	100	100	100	93
Precision	100	100	100	100	100	93
Sensitivity	100	100	100	100	100	100
Specification	100	100	100	100	100	90