# Chapter 7
# Performance Study on Real-valued Classification Problems

As mentioned in Chapter 5, the orthogonal decision boundaries of fully complex-valued neural networks help them to perform classification tasks efficiently. Therefore, in this chapter, we study the classification performance of FC-MLP and IC-MLP described in Chapter 2, FC-RBF and Mc-FCRBF explained in Chapter 3, FCRN and CC-ELM described in the chapters 5 and 6 respectively. First, the study is conducted on a set of benchmark real-valued classification problems from the UCI machine learning repository [1] and then, using a practical acoustic emission signal classification problem for health monitoring [2].

## 7.1 Descriptions of Real-valued Benchmark Classification Problems

We consider a set of real-valued benchmark problems (both multi-category/binary classification problems) from the UCI machine learning repository [1]. Based on a wide range of Imbalance Factors (I. F.) (as defined in [3]) of the data set, three multi-category and four binary data sets are chosen for this study. To recap, the imbalance factor is defined as

$$(\text{I. F.}) = 1 - \frac{C}{N} \min_{j=1,\cdots,C} N_j \tag{7.1}$$

where $N_j$ is the total number of samples belonging to the class $j$.

The detailed description of these data sets including the number of classes, the number of input features, the number of samples in the training/testing and the imbalance factor are presented in Table 7.1. From the table, one can see that the problems chosen for this study have both balanced and unbalanced data sets and also that the imbalance factors of the data sets vary over a wide range.

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**Table 7.1** Description of benchmark data sets selected from [1] for performance study

| Type of data set | Problem | No. of features | No. of classes | No. of samples | | I. F. | |
|---|---|---|---|---|---|---|---|
| | | | | Training | Testing | Training | Testing |
| Multi-Category | Image Segmentation (IS) | 19 | 7 | 210 | 2100 | 0 | 0 |
| | Vehicle Classification (VC) | 18 | 4 | 424 | 422 | 0.1 | 0.12 |
| | Glass Identification (GI) | 9 | 7 | 109 | 105 | 0.68 | 0.73 |
| Binary | Liver Disorder | 6 | 2 | 200 | 145 | 0.17 | 0.145 |
| | PIMA Data | 8 | 2 | 400 | 368 | 0.225 | 0.39 |
| | Breast Cancer | 9 | 2 | 300 | 383 | 0.26 | 0.33 |
| | Ionosphere | 34 | 2 | 100 | 251 | 0.28 | 0.283 |

## 7.2 Performance Study

First we present the performance study results on three real-valued multi-category benchmark classification problems. Next, we consider four binary benchmark classification problems.

### *7.2.1 Performance Measures*

The classification/confusion matrix $Q$ is used to obtain the statistical measures for both the class-level and global performance of the various classifiers. Class-level performance is measured by the percentage classification ($\eta_j$) which is defined as:

$$\eta_j = \frac{q_{jj}}{N_j} \times 100\% \tag{7.2}$$

where $q_{jj}$ is the total number of correctly classified samples in the class $c_j$.

The global measures used in the evaluation are the average per-class classification accuracy ($\eta_a$) and the over-all classification accuracy ($\eta_o$) defined as:

$$\begin{aligned} \eta_a &= \frac{1}{C} \sum_{j=1}^{C} \eta_j \\ \eta_o &= \frac{\sum_{j=1}^{C} q_{jj}}{\sum_{j=1}^{C} N_j} \times 100\% \end{aligned} \tag{7.3}$$

The performance of the classifiers are compared using these class-level and global performance measures.

### *7.2.2 Multi-category Real-valued Classification Problems*

As the complex-valued networks are shown to have better computational power than the real-valued networks [4], the classification performance of the complex-valued learning algorithms are compared against well-known real-valued classifiers, available in the literature for these problems. The real-valued classifiers used for comparison are the Support Vector Machines (SVM) [5], the minimal resource allocation network (MRAN) [6], the growing and pruning radial basis function network (GAP-RBFN) [7], the online sequential extreme learning machine (OS-ELM) [8], the real coded genetic algorithm based extreme learning machine [9], the Sequential Multi-Category Radial Basis Function (SMC-RBF) [10] and the Self-adaptive Resource Allocation Network (SRAN) [11]. The "*asinh*" and "*atan*" activation functions are observed to be better than the other ETF's and they are chosen as activation functions in the hidden layer for the FC-MLP and IC-MLP. The results of the RCGA-ELM is reproduced from [9], while those of the other real-valued classifiers are reproduced from [10]. The classification results for the PE-CVNN are reproduced from [12], while the results of the MLMVN are generated using the software simulator available in the author's web site [1].

Table 7.2 presents the overall and average testing efficiencies of the various classifiers on the three multi-category benchmark classification problems chosen for this study. In this study, the complex-valued input features ($z$) for FC-MLP, IC-MLP, FC-RBF and Mc-FCRBF are obtained by phase encoding the real-valued input features ($x$) in $[0,\pi]$ [13] using the transformation:

$$z = exp(i\phi) = cos\,\phi + isin\,\phi, \text{ where } \phi = \frac{\pi(x-a)}{b-a};\ a,b \in \mathbb{R} \text{ and } x \in [a,b]. \quad (7.4)$$

The input features for CC-ELM and FCRN classifiers are obtained by using the circular transformation defined in Eq. (6.19).

From the table, it is clear that the complex-valued classifiers outperform all the existing real-valued classifiers. The superior performance of the complex-valued classifiers can be attributed to their orthogonal decision boundaries. The higher performance of the complex-valued classifiers is very obvious in the glass identification problem which has a highly unbalanced data set.

Following observations emerge from the Table 7.2:

- FC-MLP, IC-MLP, FC-RBF, Mc-FCRBF, FCRN and CC-ELM classifiers outperform other complex-valued classifiers: MLMVN and PE-CVNN The performances of MLMVN [14] and PE-CVNN [13] may be limited because of the following factors:

[1] http://www.eagle.tamut.edu/faculty/igor/Downloads.htm

- The activation functions used in the PE-CVNN are similar to those used in the split complex-valued neural networks. Therefore, the correlation between the real and imaginary parts of the error are not considered in the network parameter update and the gradients are not fully complex-valued [15]. The limitations of using the split complex-valued activation functions have been discussed in detail in section 2.1.1.
- The complex-valued Multi Layer Multi Valued Network (MLMVN) that employs the multi-valued neurons uses a derivative free global error correcting learning rule to update the network parameters [14]. In MLMVN, the normalized real-valued input features ($x$) are mapped on to a full unit circle using $exp(i2\pi x)$ and the class labels are encoded by the roots of unity in the Complex plane. However, as the input features are mapped on to a full unit circle, this mapping results in the same complex-valued features for the real-valued features with values 0 and 1 (transformation is not unique). In addition, the multi-valued neurons map the complex-valued inputs to $C$ discrete outputs on the unit circle. As number of classes ($C$) increases, the areas of the sectors per class within the unit circle decreases which results in a higher misclassification rate.

- Comparing the performances of FC-MLP and IC-MLP classifiers, IC-MLP classifier outperforms FC-MLP classifier in all the three benchmark problems considered. While the "*atan*" activation function resulted in a better classification of the IS data set, the "*asinh*" activation function outperforms the "*atan* " activation function in the classification of the unbalanced VC and GI data sets.
- FC-RBF classifier performs better than FC-MLP and IC-MLP classifiers in all the three problems. This is because the $sech(.)$ function used in FC-RBF has a magnitude response that is similar to that of the Gaussian function and has similar localization properties of the Gaussian activation function. This aids in improving the classification ability of FC-RBF classifier compared to that of the FC-MLP/IC-MLP classifiers.
- Mc-FCRBF classifier performs better than FC-RBF classifier along with a reduced computational effort. The self-regulatory system chose 155 of the total 210 samples for classification of the image segmentation problem which has a well-balanced data set. The self-regulatory system selects 358 of the total 422 samples and 272 of the total 336 samples to train Mc-FCRBF classifier for the vehicle classification and glass identification problems, respectively.
- CC-ELM classifier outperforms all the real-valued/complex-valued classifiers used in this study. It also requires the lowest computational effort in all the three real-valued benchmark classification problems. This can be attributed to the presence of the circular transformation that transforms the real-valued input features to all the four quadrants of the Complex domain uniquely and the learning algorithm that finds the optimum solution to the set of linear equations formed at the output layer. The best performance of CC-ELM can be distinctively seen in the glass identification problem which has a highly unbalanced data set.

- The performance of FCRN is slightly better than CC-ELM and is much better than the other classifiers. This can be attributed to the fact that FCRN uses the logarithmic error function, while the other classifiers use the mean squared error function.

### *7.2.3 Binary Real-valued Classification Problems*

Next, we present the results of the binary benchmark classification problems listed in Table 7.1. Since it has been observed from the study on multi-category benchmark problems that FC-RBF and Mc-FCRBF outperform the FC-MLP and IC-MLP classifiers, we only compare the classification performances of FC-RBF and Mc-FCRBF classifiers in comparison with other real-valued classifiers. Performance results of SVM, ELM, SRAN, FC-RBF, Mc-FCRBF, FCRN and CC-ELM classifiers are presented in Table 7.3. From the results, one can see that the complex-valued classifiers, FC-RBF, Mc-FCRBF and CC-ELM classifiers outperformed the real-valued classifiers (SVM, ELM and SRAN) available in the literature. Among the complex-valued classifiers, CC-ELM and FCRN classifiers perform better than the other complex-valued classifiers considered in the study with the lower computational effort.

## 7.3 Performance Study Using a Real-world Acoustic Emission Classification Problem

Acoustic emission signals are the electrical versions of the stress or pressure waves produced by sensitive transducers. These waves are produced due to the transient energy release caused by the irreversible deformation processes in the material [2]. Different sources of acoustic emission exist and these sources can be characterized by the acoustic signals. The classification of acoustic emission signals based on their sources is a very difficult problem, especially in the real world where ambient noise and pseudo acoustic emission signals exist. Even in a noise free environment, superficial similarities exist between the acoustic emission signals produced by different sources making the classification task cumbersome.

In the study conducted in [2], noise free burst type acoustic emission signal from a metal surface is assumed. The data set presented in [2] uses 5 input features to classify the acoustic signals to one of the 4 sources, i.e., the pencil source, the pulse source, the spark source and the noise. A training data set with 62 samples and testing data set with 137 samples are used for the acoustic emission signal classification problem. For details of the input features and the experimental set up used in the data collection, refer to [2].

Table 7.4 presents the performance results of the complex-valued FC-RBF, Mc-FCRBF, FCRN and CC-ELM classifiers in comparison to the best results available in the literature for the acoustic emission signal classification problem, viz., the Fuzzy K-means clustering algorithm [2], ant colony optimization algorithm [16]

**Table 7.2** Benchmark classification problems: Performance comparison of the SR-FC-RBF classifier with other classifiers

| Problem | Domain | Classifier | $h$ | Time (sec.) | Testing | |
|---|---|---|---|---|---|---|
| | | | | | $\eta_o$ | $\eta_a$ |
| IS | Real | SVM | 96 | 721 | 90.62 | 90.62 |
| | | MRAN | 76 | 783 | 86.52 | 86.52 |
| | | GAP-RBFN | 83 | 365 | 87.19 | 87.19 |
| | | OS-ELM | 100 | 21 | 90.67 | 90.67 |
| | | RCGA-ELM | 50 | - | 91 | 91 |
| | | SMC-RBF | 43 | 142 | 91 | 91 |
| | | SRAN | 47 | 22 | 92.3 | 92.3 |
| | Complex | PE-CVNN | - | - | 93.2[2] | - |
| | | MLMVN | 80 | 1384 | 83 | - |
| | | FC-MLP($asinh$) | 80 | 374 | 91.57 | 91.57 |
| | | FC-MLP($atan$) | 75 | 359 | 90.48 | 90.48 |
| | | IC-MLP($asinh$) | 80 | 390 | 91.81 | 91.81 |
| | | IC-MLP($atan$) | 80 | 385 | 92.81 | 92.81 |
| | | FC-RBF | 38 | 421 | 92.33 | 92.33 |
| | | Mc-FCRBF | 36 | 362 | 92.9 | 92.9 |
| | | FCRN | 70 | 0.4 | 93.3 | 93.3 |
| | | CC-ELM | 60 | 0.03 | 93.2 | 93.2 |
| VC | Real | SVM | 234 | 550 | 68.72 | 67.99 |
| | | MRAN | 100 | 520 | 59.94 | 59.83 |
| | | GAP-RBFN | 81 | 452 | 59.24 | 58.23 |
| | | OS-ELM | 300 | 36 | 68.95 | 67.56 |
| | | SMC-RBF | 75 | 120 | 74.18 | 73.52 |
| | | SRAN | 113 | 55 | 75.12 | 76.86 |
| | Complex | PE-CVNN | - | - | 78.7[3] | - |
| | | MLMVN | 90 | 1396 | 78 | 77.25 |
| | | FC-MLP($asinh$) | 75 | 530 | 76.07 | 77.49 |
| | | FC-MLP ($atan$) | 70 | 462 | 73.22 | 73.83 |
| | | IC-MLP($asinh$) | 75 | 612 | 79.62 | 80.38 |
| | | IC-MLP ($atan$) | 70 | 574 | 74.17 | 74.26 |
| | | FC-RBF | 70 | 678 | 77.01 | 77.46 |
| | | Mc-FCRBF | 70 | 638 | 77.72 | 77.58 |
| | | FCRN | 90 | 0.8 | 82.62 | 82.46 |
| | | CC-ELM | 85 | 0.1084 | 82.23 | 82.52 |
| GI | Real | SVM | 102 | 320 | 64.23 | 60.01 |
| | | MRAN | 51 | 520 | 63.81 | 70.24 |
| | | GAP-RBFN | 75 | 410 | 58.29 | 72.41 |
| | | OS-ELM | 60 | 15 | 67.62 | 70.12 |
| | | SMC-RBF | 58 | 97 | 78.09 | 77.96 |
| | | SRAN | 59 | 28 | 86.21 | 80.95 |
| | Complex | PE-CVNN | - | - | 65.5[b] | - |
| | | MLMVN | 85 | 1421 | 73.24 | 66.83 |
| | | FC-MLP($asinh$) | 70 | 338 | 80.95 | 79.60 |
| | | FC-MLP($atan$) | 70 | 346 | 80 | 79.09 |
| | | IC-MLP($asinh$) | 80 | 390 | 82.86 | 80.55 |
| | | IC-MLP($atan$) | 70 | 356 | 81.90 | 82.97 |
| | | FC-RBF | 90 | 452 | 83.76 | 80.95 |
| | | Mc-FCRBF | 85 | 364 | 83.91 | 80 |
| | | FCRN | 90 | 0.25 | 94.5 | 88.3 |
| | | CC-ELM | 100 | 0.08 | 94.44 | 84.52 |

**Table 7.3** Performance comparison on benchmark binary classification problems

| Problem | Classifier Domain | Classifier | $h$ | Training Time (s) | Testing Efficiency ($\eta_o$) |
|---|---|---|---|---|---|
| Breast cancer | Real-valued | SVM | 190 | 0.1118 | 94.20 |
| | | ELM | 65 | 0.1442 | 96.28 |
| | | SRAN | 7 | 0.17 | 96.87 |
| | Complex-valued | FC-RBF | 10 | 158.3 | 97.12 |
| | | Mc-FCRBF | 10 | 125 | 97.4 |
| | | FCRN | 15 | 0.16 | 97.4 |
| | | CC-ELM | 15 | 0.0811 | 97.39 |
| Iono-sphere | Real-valued | SVM | 30 | 0.0218 | 90.18 |
| | | ELM | 25 | 0.0396 | 88.78 |
| | | SRAN | 21 | 3.7 | 90.84 |
| | Complex-valued | FC-RBF | 10 | 186.2 | 89.48 |
| | | Mc-FCRBF | 10 | 152 | 90 |
| | | FCRN | 15 | 0.0624 | 92.03 |
| | | CC-ELM | 15 | 0.0312 | 92.43 |
| Liver disorders | Real-valued | SVM | 158 | 0.0972 | 68.24 |
| | | ELM | 132 | 0.1685 | 71.79 |
| | | SRAN | 91 | 3.38 | 66.9 |
| | Complex-valued | FC-RBF | 20 | 133 | 74.6 |
| | | Mc-FCRBF | 20 | 112 | 76.6 |
| | | FCRN | 10 | 0.05 | 75.86 |
| | | CC-ELM | 10 | 0.059 | 75.5 |
| PIMA data | Real-valued | SVM | 209 | 0.205 | 76.43 |
| | | ELM | 218 | 0.2942 | 76.54 |
| | | SRAN | 97 | 12.24 | 78.53 |
| | Complex-valued | FC-RBF | 20 | 130.3 | 78.53 |
| | | Mc-FCRBF | 20 | 103 | 79.89 |
| | | FCRN | 15 | 0.125 | 80.71 |
| | | CC-ELM | 20 | 0.073 | 81.25 |

and genetic programming [17]. The results show that the complex-valued classifiers outperform the real-valued classifiers considered in this study. It can also be seen that CC-ELM and FCRN classifiers required only 10 neurons to achieve an over-all testing efficiency of 99.27%, which is about 6% better than the best results reported in the literature for this problem. Thus, CC-ELM and FCRN perform an efficient classification of the acoustic emission signals using a compact network.

**Table 7.4** Performance comparison results for the acoustic emission problem

| Classifier domain | Classifier | Testing | |
|---|---|---|---|
| | | $\eta_o$ | $\eta_{av}$ |
| Real-valued | Fuzzy C-Means Clustering | | 93.34 |
| Complex-valued | FC-RBF | 96.35 | 95.2 |
| | Mc-FCRBF | 98.54 | 97.83 |
| | FCRN | 99.27 | 98.91 |
| | CC-ELM | 99.27 | 99.17 |

## 7.4 Summary

In this chapter, we studied the decision making ability of FC-MLP, IC-MLP, FC-RBF, Mc-FCRBF, FCRN and CC-ELM learning algorithms in comparison to other complex-valued classifiers, MLMVN and PE-CVNN. The study was performed using a set of multi-category and binary benchmark classification data sets from the UCI machine learning repository and a practical acoustic emission classification problem. Performance results show that the performance of the complex-valued classifiers are better than the real-valued classifiers available in the literature. The orthogonal decision boundaries of the complex-valued classifiers help them to outperform the real-valued classifiers. However, the performance of the complex-valued classifiers are affected due to the transformation used to convert the real-valued input features to the Complex domain, the activation function used at the hidden layer, and the nature of the learning algorithm. It was also observed that the circular transformation, which maps the real-valued input features to the Complex domain uniquely, is better than the phase encoded transformation and the bilinear transformation.

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