USE OF ARTIFICIAL NEURAL NETWORK FOR THE SELECTION OF SALES INTERMEDIARIES

O. Saracoglu and I. Topcu*
Department of Industrial Engineering
Istanbul Technical University, Turkey
orhan.saracoglu@itu.edu.tr
ilker.topcu@itu.edu.tr

ABSTRACT

Recently, compliance and regulation has been number one threat; not only for the area of financial services, but also across a spectrum of sectors, ranging from oil and gas, through life sciences and technology to automotive. The main reason for the tougher stand against corrupt business practices is the increased enforcement actions against companies. When companies go global and extend their network in different countries, they will surely get into business relationships with third parties, especially sales intermediaries. Therefore, all companies have to pay special attention to the selection process of their ethical business partners. A systematic detailed check of the prospective sales intermediaries questioning their economical, legal and ethical aspects, aiming to reveal any issue which could cast doubt on the integrity is called due diligence. This costly examination usually carried forth by external professionals has become a business standard of almost all multi-national companies.

In this study, a practical decision support tool using pattern recognition of artificial neural networks is developed to assist companies in their selection of sales intermediaries by way of minimizing any future risk of a compliance and regulation violation, which could result in severe sanctions and punishments against such companies.

* Corresponding Author
1 INTRODUCTION

In the last decade, the risk of not complying with the local and international legislation has significantly increased: “compliance and regulation” was rated as one of the most prominent risks. In 2009, this risk was exceeded only by worries about the credit crunch in the market within the crisis environment. In 2010, “regulation and compliance” has resumed its place as the number one threat; not only for the area of financial services, but also across a spectrum of sectors, ranging from oil and gas, through life sciences and technology to automotive. The main reason for the tougher stand against corrupt business practices is the increased enforcement actions against companies.

When companies go global and extend their network in different countries, they will surely get into business relationships with third parties, especially sales intermediaries (SIs). Therefore, all companies have to pay special attention to the selection process of their “ethical” business partners. A systematic detailed check of the prospective SI questioning their economical, legal and ethical aspects, aiming to reveal any issue which could cast doubt on the integrity is called “due diligence”. This costly examination usually carried forth by external professionals has become a business standard of almost all multi-national companies.

In this study, a practical decision support tool using pattern recognition of Artificial Neural Networks (ANNs) is developed to assist companies in their selection of SIs by way of minimizing any future risk of a “compliance and regulation” violation, which could result in severe sanctions and punishments against such companies.

Within the anti-corruption legislative environment and increasing enforcement of Foreign Corrupt Practices Act (FCPA), United Nations Convention Against Corruption (UNCAC) and anti-bribery convention of OECD (Organization for Economic Cooperation and Development); this study emphasizes the importance of adherence to the legislative regulations and provides a practical management decision support tool using the “pattern recognition” approach of the provided ANNs that is developed. Then, the model is trained based on the existing data and finally successfully applied for selection of the new SIs which is the main part of due diligence process.

2 THIRD PARTY FCPA DUE DILIGENCE

FCPA is a U.S. law that has been in existence since the 1970s, when investigations by the Securities and Exchange Commission (SEC) showed U.S. companies engaged in illegal payments exceeding $300 million to foreign government officials. The passage of the FCPA was intended to stop these improper payments and to ensure a fair playing field for overseas business dealings [1].

The FCPA’s premise is simple: The FCPA makes it illegal for a U.S. company, U.S. individual, or foreign corporation that has a class of securities registered, or that is required to file reports under the Securities and Exchange Act of 1934, to make payments to a foreign official to obtain or retain business or to gain an improper business advantage. Public companies should accurately and fairly reflect the transactions of a corporation on its books and records, and maintain an adequate system of internal accounting controls.

The FCPA makes it unlawful to bribe foreign government officials to obtain or retain business. There are five elements in the basic prohibition, which must be met to constitute a violation of the act [2]: corrupt intent, affected entities and individuals, payment, recipient, and business purpose. The FCPA also prohibits corrupt payments through intermediaries [2]. It is unlawful to make a payment to a third party, while knowing that all or a portion of the payment will go directly or indirectly to a foreign government official. The term “knowing” includes conscious disregard and deliberate ignorance. The elements of an offense are essentially the same as described above, except that in this case the “recipient” is the intermediary who is making the payment to the requisite “foreign official.”
Intermediaries may include joint venture partners or agents. To avoid being held liable for corrupt third party payments, U.S. companies are encouraged to exercise due diligence and to take all necessary precautions to ensure that they have formed a business relationship with reputable and qualified partners and representatives. Such due diligence may include investigating potential foreign representatives and joint venture partners to determine if they are in fact qualified for the position, whether they have personal or professional ties to the government, the number and reputation of their clientele, and their reputation with the U.S.

SEC is in charge of enforcing violations of the accounting provisions while the U.S. Department of Justice (DOJ) is primarily responsible for enforcing the anti-bribery provisions [2]. Both agencies can institute civil actions, but only the DOJ is authorized to file criminal charges. There are severe punishments for entities as well as individuals for the violation of anti-bribery provisions and the violation of accounting provisions. Failure to comply with the regulations can result in prison sentences and substantial fines.

To comply with the regulations and to avoid FCPA risks, entities should give importance to due diligence when they get interaction with third parties. “Due diligence” is a term used for a number of concepts involving either an investigation of a business or person prior to signing a contract, or an act with a certain standard of care. It can be a legal obligation, but the term will more commonly apply to voluntary investigations. A common example of due diligence in various industries is the process through which a potential acquirer evaluates a target company or its assets for acquisition [3]. In other words, it is an information gathering procedure (entity's ownership, background, financial standing, etc.) required in connection with the retention of a third party and used to assess the third party's integrity, reputation, technical competence, and ability to perform the work in question in a manner that fully complies with relevant laws. This is done in order to avoid potential liability for the conduct of third parties representing the company.

One of the third parties of an entity is an SI. SI means any outside concern, which a company uses, directly or indirectly, either for a particular transaction or on a continuing basis [3], to provide services in obtaining purchase orders for products or services, to assist company in implementing sales transactions, or to sell or resell products or services. SI can be a distributor, a dealer, a vendor, a service center, a body builder, or an assembler as well as a sales representative, an agent or a consultant.

Some may believe that a basic database check and cursory media survey is sufficient, but this is not necessarily the case. The fact is that politically exposed persons (people currently or recently holding public positions or performing important public functions, such as senior diplomats, governmental officials, high-level leaders of religious or political organizations, members of ruling royal families, military leaders or judges) are not always identified by global database checks, nor do they necessarily appear in media coverage. The company expects the same from their business partners as from their employees: Integrity in all their actions. To ensure this at the outset, all business partners must undergo compliance due diligence review before a business relationship is entered into. Particularly if business partners act on behalf of the company, their reputation and previous conduct in business life must meet the toughest requirements.

In the widely used questionnaire-based assessment, the commissioning unit, the local compliance manager (if there is one) and the new SI are asked to provide detailed information on various topics in questionnaires. For example, details regarding business and management, ownership structure and remuneration system as well as potential conflicts of interest or compliance issues are requested. Finally, this information is used to examine the business partner, paying particular attention to warning signals (red flags). If warning signals such as unethical conduct in the past or signs of involvement in cases of corruption arise, they are examined, assessed and documented. The specialist department obtains approval to commence the planned business relationship from a compliance point of view with regard
to this specific partner only when all outstanding issues are resolved. After that, contract negotiations can be started. Otherwise, collaboration with the business partner is neither desirable nor permissible. Overall, this process enables a detailed check of the prospective business partner.

3  ARTIFICIAL NEURAL NETWORKS

ANNs are mathematical or computational models that are inspired by the structure and functional aspects of biological neural networks [4]. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases, ANNs are adaptive systems that change its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

ANNs are effective and reliable algorithms capable of performing functional input and output mappings [5]. Their parallel, multi-parametric characters, and computing speed, make them a powerful computational tool especially when the underlying physical-mathematical models are complicated. After training, ANNs can be used to predict the outcome of new independent input data. ANNs imitate the learning process of the human brain and can process problems involving complex data with non-linear relations even if the data are imprecise and noisy. Thus, they are ideally suited for the modeling of complex models that include numerous non-linear inputs.

Since late 1990’s there has been a substantial increase in the interest on ANNs. ANNs have been applied successfully in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, and many others [6]. ANNs have been used for a wide variety of applications where statistical methods are traditionally employed. They have been used in classification problems, such as identifying underwater sonar currents, recognizing speech, predicting the secondary structure of globular proteins and even iris recognition [7].

In time-series applications, ANNs have been used for predicting stock market performance. As statisticians or users of statistics, these problems are normally solved through classical statistical methods, such as discriminant analysis, logistic regression, Bayes analysis, multiple regression, and time-series models. It is, therefore, time to recognize neural networks as a powerful tool for data analysis. They have been also used in a wide range of applications including pattern classification, function approximation, optimization, prediction and automatic control and many other engineering problems [8]. This method learns from given examples by constructing an input-output mapping in order to perform predictions. In other words, to train and test a neural network, input data and corresponding output values are necessary [9]. ANNs can be trained to overcome the limitations of the conventional approaches to solve complex problems that are difficult to model analytically.

ANNs were also used in a wide area. For instance, Angelini et al. [10] described the case of a successful application of ANNs to credit risk assessment in accordance with the Basel Committee on Banking Supervision. ANN and data mining techniques to construct the financial distress prediction model was also applied by Chen and Du [11]. Khashman [12] applied emotional ANN which has been suggested for satisfactory pattern recognition and compared the performance of emotional ANNs to that of conventional ANNs when applied to credit risk evaluation. Romdhane and Ayeb [13] developed a backpropagation ANN based approach for customer profiling. Selection of the major driving forces of inflation among all the driving forces that were revealed through a cognitive map is realized through ANNs [14]. For an integrated transportation decision support system for transportation policy decisions, the causal relationships between variables that have non-linearity and multi collinearity in their nature were determined by using ANNs [15]. For the clustering of countries, the relationships between the criteria and the classification of countries were determined by
using ANNs [16]. The importance of the criteria for complex problems like criteria affecting country’s efficiency score can be also determined by ANNs [17]. ANNs show excellent performance on pattern recognition tasks and they were suggested over statistical methods [18].

In ANN analysis, a set of the input patterns are set aside for testing training the network and the rest of the patterns are used for testing and validating the network performance. The important point in selecting the training sample is that the input patterns selected as the training set should be representative of the population and the underlying structure [19]. Inappropriate selection can cause a faultily configured network and thus low performance. There is no consensus in literature on the determination of the training sample and test sample sizes. Most researchers select the training and testing and validation sets on the rule of 90 % vs. 10 %, or, 80 % vs. 20 %, or 70 % vs. 30 % [20]. Although as the sample size gets larger, the accuracy of the results get better [21]; in reality, the sample size is constrained by the data in hand. Zhang et al. [20], state that with a large enough sample ANNs can model any complex structure in data and can benefit from large samples than linear statistical models can. ANNs do not necessarily require a larger sample than is required by linear models in order to perform well. Zhang et al. [20], state that ANN forecasting models perform quite well even when the sample size is less than 50, while the linear models typically require more [22].

4 A PROPOSITION OF AN ANN MODEL FOR THE SELECTION OF THE SALES INTERMEDIARIES

As aforementioned; to provide a practical management decision support tool, an ANN pattern recognition based framework is developed and successfully applied in due diligence process for the selection of the SIs. In this study; since the set of input patterns for the network training is available, the supervised backpropagation learning methodology of the ANNs training is used. Backpropagation learning consists of two passes through the different layers of the network; a forward pass and a backward pass.

The questions used for the selection of the SIs are defined from the due diligence questionnaires used widely by the dignitary professional services firms, intelligence and investigations companies and risk advisors worldwide. There are 29 questions, which can be answered either as “no” or as “yes”, whereas some of the questions can also be answered as “partial” as shown in Table 1. As can be seen from the table, an undesirable state is represented by 0 while a desirable state is represented by 1.

At the end of the evaluation, three different decisions for the proposed business relationship with the SI can be achieved as follows:

- Business with the SI is not recommended (result score: 0)
- Business with the SI is permitted, but watch the SI carefully (result score: 0.5)
- Business with the SI is permissible (result score: 1)
Table 1. Sales Intermediary Evaluation Questionnaire

<table>
<thead>
<tr>
<th>No</th>
<th>Questions</th>
<th>Evaluation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Does the SI have a clear and comprehensible address?</td>
<td>No 0.0</td>
</tr>
<tr>
<td>2</td>
<td>Does the SI have a Valid Business Registration Certificate?</td>
<td>No 0.0</td>
</tr>
<tr>
<td>3</td>
<td>Does the SI have a list of banks with which the company has a financial relationship and related “good-standing” letter?</td>
<td>No 0.0</td>
</tr>
<tr>
<td>4</td>
<td>Is the SI in a Good Financial Status?</td>
<td>No 0.0</td>
</tr>
<tr>
<td>5</td>
<td>Do the owners and shareholders of the SI has governmental and political ties?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>6</td>
<td>Were any of the owners, shareholders, officers or directors charged or convicted of the with fraud or bribery?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>7</td>
<td>Is the SI recommended by a government official?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>8</td>
<td>Will signature of standard anti-bribery clauses exist in the proposed contract?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>9</td>
<td>Does the SI have a clear description of the tasks/services?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>10</td>
<td>Does the SI have the resources (staff/facility) and industry/technical experience for the proposed business?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>11</td>
<td>Does SI expect a lump sum payment for the activities to be performed?</td>
<td>1.0 0.5 0.0</td>
</tr>
<tr>
<td>12</td>
<td>Does SI expect a commission payment based on a contract?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>13</td>
<td>Are the services and duties of the SI comparable and plausible to the industry standards?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>14</td>
<td>Will the proposed payment method to the SI be via bank transfer?</td>
<td>0.0 n.a.  1.0</td>
</tr>
<tr>
<td>15</td>
<td>Will the proposed payment method to the SI be as cash?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>16</td>
<td>Does the SI expect an upfront payment?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>17</td>
<td>Did the SI suggest anything unusual “to get the business”?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>18</td>
<td>Is there any local law or policy that prohibits the relation with the proposed SI?</td>
<td>0.0 n.a.  1.0</td>
</tr>
<tr>
<td>19</td>
<td>Is there any indications or allegations of illegal or unethical conduct of the SI?</td>
<td>1.0 0.5 0.0</td>
</tr>
<tr>
<td>20</td>
<td>Are you aware that the SI share his remuneration with any other 3rd party?</td>
<td>1.0 n.a.  0.0</td>
</tr>
<tr>
<td>21</td>
<td>Does the SI have good reputation based on the evaluation of the press reports?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>22</td>
<td>Is the SI publicly listed?</td>
<td>0.0 1.0</td>
</tr>
<tr>
<td>23</td>
<td>What is the percentage of SI's capacity that will be devoted to the proposed business relationship? (0: &gt;80%, 0.5: = %50-80, 1: &lt;=%50)?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>24</td>
<td>The number employees of the SI? (0: &lt;6, 0.5: = 6-20, 1: &gt;20)</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>25</td>
<td>Does the SI have a clear organization chart?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>26</td>
<td>Does the SI have a clear definition of the principle lines of business?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>27</td>
<td>Does the SI have any internal compliance regulations, policies and guidelines?</td>
<td>0.0 0.5 1.0</td>
</tr>
<tr>
<td>28</td>
<td>Is the SI able to provide 5 generally knows references?</td>
<td>0.0 n.a.  1.0</td>
</tr>
<tr>
<td>29</td>
<td>Is the SI an incorporated company?</td>
<td>0.0 n.a.  1.0</td>
</tr>
</tbody>
</table>

n.a.: not available

As the aim is to develop a tool as a decision support tool, use of actual data for the training, validating and testing is needed. Accordingly, 584 different anonymous SI decisions that are provided based on the questions. The data gathered from a consultant company and is a result of actual evaluations completed worldwide. 409 instances of 584 total available actual data set (70%) is used for the training, 117 of 584 data (20%) is used for the validation. The remaining 58 instances (10%) are used for the test procedure to evaluate the success of the training. To summarize, the learning set is used for creating a model, validation set is used for verifying the model, and the testing set is used for performance of the usability of the model. In other words, training data is repeatedly used to estimate the weights (includes biases) of candidate designs, validation data repeatedly used to estimate the non-training data performances, and testing data repeatedly used to evaluate the model performance on data not seen during training.
performance error of candidate designs and also used to stop training once the non-training validation error estimate stops decreasing. Test data used once and only once on the best design to obtain an unbiased estimate for the predicted error of unseen non-training data.

For the application of the ANN model, Neural Network Pattern Recognition Tool of the MATLAB’s Product Family is used. MATLAB is a product of MathWorks company, who is the leading developer of mathematical computing software for engineers and scientists, headquarters in Natick, Massachusetts, U.S. [23].

The Neural Network Pattern Recognition Tool is created as provided in Appendix. The pattern recognition model is structured with 2, 3, and 4 hidden neurons for the training with the actual data. Accordingly, the results and validation performances using different hidden neuron numbers are compared and evaluated.

Training a neural network to learn patterns in the data involves iteratively presenting it with examples of the correct known answers. The objective of training is to find the set of weights between the neurons that determine the global minimum of error function. This involves decision regarding the number of iteration i.e., when to stop training a neural network and the selection of learning rate (a constant of proportionality which determines the size of the weight adjustments made at each iteration) and momentum values (how past weight changes affect current weight changes).

The result output of the training with 2 hidden neurons is shown in Figure 1.

![Figure 1. Result Confusion Matrix using 2 Hidden Neurons](image)

Figure 1 shows the confusion matrices for training, testing, validation and combined result data by using 2 hidden neurons. The diagonal cells in each table show the number of cases that were correctly classified, and the off-diagonal cells show the misclassified cases. The lower right cell shows the total percent of correctly classified cases (diagonal cells) and the
The total percent of misclassified cases (off-diagonal cells). The results for all three data sets (training, validation, and testing) show very good recognition. The high number of responses in the diagonal cells indicates that the pattern has been successfully trained by the ANN model.

The result of the training confusion matrix shows that in total 409 data are successfully trained by the model (target and output numbers matched). The result of the validation confusion matrix in Figure 1 shows that; as the model measures the difference to validate whether the learning of the network can be finished or not, 5 (sum of 2, 1, 1 and 1 in the red cells) out of 117 output did not match the target. The number “1” in the first column - second row of the validation confusion matrix means: during validation of the training, 1 data of the validation set produced a incorrect output. Similarly, the number “2” in the third column - second row of the validation confusion matrix means: during validation of the training, 2 data of the validation set produced an incorrect output. The percentage in the lower right cell of the validation confusion matrix means that with 95.7% success the validation has been completed. The result of the test confusion matrix in Figure 1 shows the performance of the ANN model whether the network is able to work also on the data that were not used in the previous process. In this matrix, only 3 (in off-diagonal cells) out of 58 outputs did not match the target. The number “2” in the first column - second row of the test confusion matrix means: during testing, 2 data of the testing set produced a incorrect output. Similarly, the number “1” in the first column - third row of the test confusion matrix means: during testing, 1 datum of the testing set produced an incorrect output. The percentage in the lower right cell of the test confusion matrix means that with 94.8% success. The result of the all confusion matrix in Figure 1 shows a sum of all other three matrices, which are the training confusion matrix, validation confusion matrix and test confusion matrix. As a result, the percentage in the lower right cell of the all confusion matrix shows that the pattern recognition network training of the ANN model was completed with 98.5% success.

The Figure 2 shows the best validation performance is occurred by iteration 126 whereat the final mean-square error is small (0.0306).

![Figure 2. Validation Performance Result using 2 Hidden Neurons](image)

Within the same logic, the number of hidden neurons is increased to 3. The result output of the training with 3 hidden neurons is shown in Figure 3. Figure 4, on the other hand, shows the best validation performance is occurred by iteration 56 whereat the final mean-square error is small (0.00562).
When the number of hidden neurons is increased to 4, the result output of the training with 4 hidden neurons given in Figure 5 is revealed. The Figure 6 shows the best validation performance is occurred by iteration 51 where the final mean-square error is small (0.0066).

According to the confusion matrices for training, testing, validation and combined result data by using 2, 3, and 4 hidden neurons; the best recognition (the number of cases that are correctly classified) is achieved when 3 hidden neurons are used (Table 2).
Figure 5. Result Confusion Matrix using 4 Hidden Neurons

Figure 6. Validation Performance Result using 4 Hidden Neurons

Table 2. Comparison of the Testing Results with Different Hidden Neurons

<table>
<thead>
<tr>
<th>Number of hidden neurons</th>
<th>Training success</th>
<th>Validation success</th>
<th>Testing success</th>
<th>All confusion success</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>99.8%</td>
<td>95.7%</td>
<td>94.8%</td>
<td>98.5%</td>
</tr>
<tr>
<td>3</td>
<td>100%</td>
<td>99.1%</td>
<td>100%</td>
<td>99.8%</td>
</tr>
<tr>
<td>4</td>
<td>99.5%</td>
<td>97.4%</td>
<td>93.1%</td>
<td>98.5%</td>
</tr>
</tbody>
</table>
5 CONCLUSION

The major purpose of this study is to develop a practical management decision support tool that assists the companies to select their SIs via due diligence process by minimizing the future risk of the FCPA violation, which results in severe sanctions and punishments to the companies. As also pointed out in the “Business Risk Report 2010” held by Ernst & Young Global [24], “regulation and compliance” expected to be the number one risk factor of the (especially) multi-national companies. When the multi-national companies go global and extend their network in different countries, they will expectedly get into business relationship with numerous third parties, especially SIs. As the biggest FCPA risk originates from the SIs, in this study, the application of the ANN model to the selection of SIs is focused on.

The due diligence process for SIs are held today mainly by professional companies, which requires significant monetary resources. By using the proposed decision support tool using pattern recognition of ANN, the users will benefit from the pattern of the already resulted SI decisions, which contains the experience and knowledge. The performance of the developed ANN model for new data resulted in an almost intact correct outcome, which increases the confidence about the usability of the ANN model as a management decision support tool in the companies. The companies, which require due diligence process for the selection of SIs, need to setup their own ANN model within a mathematical programming application (within this study MATLAB is used) and let the ANN model be trained from the existing decisions. After the model is trained, the model will propose a decision to the management of the company. Whenever the company plans to get into a business relationship with a new SI, by using the trained tool, it will accordingly enable the company save significant monetary resources from consultancy expenses.

This study has a pioneer view and is a unique synthesis of a decision support system tool and due diligence process for the selection of the SIs. As a further suggestion, the application of the ANN model shall be broadened to other third parties of the companies such as vendors, law firms, accounting firms which also require due diligence performance in order to mitigate any “compliance and regulation” associated risks. Moreover, application of other decision-making approaches shall provide the evaluation of the effects of individual criteria to the decision process and the results can be compared with those of this study.

6 REFERENCES


[23] The web site for MATLAB (http://www.mathworks.com)

APPENDIX: ANN Model and Parameters for the Sales Intermediary Selection in Neural Network Pattern Recognition Tool

function net = create_pr_net(inputs, targets)
%CREATE_PR_NET Creates and trains a pattern recognition neural network.
% NET = CREATE_PR_NET(INPUTS,TARGETS) takes these arguments:
% INPUTS - RxQ matrix of Q R-element input samples
% TARGETS - SxQ matrix of Q S-element associated target samples, where
% each column contains a single 1, with all other elements set to 0.
% and returns these results:
% NET - The trained neural network
% Create Network
numHiddenNeurons = 3; % Adjust as desired; 2, 4 and 5 were also tested
net = newpr(inputs, targets, numHiddenNeurons);
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 20/100;
net.divideParam.testRatio = 10/100;
net.trainParam.epochs = 3000;
net.trainParam.max_fail = 20;
% Train and Apply Network
[net, tr] = train(net, inputs, targets);
outputs = sim(net, inputs);
perf = tr;
% Plot
plotperf(perf)
plotconfusion(targets, outputs)